Validation of a Building Simulation Tool for Predictive Control in Energy Management Systems

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"When one door closes, another door opens; but we so often look so long and regretfully upon the closed door, that we do not see the ones which open for us."

AGB

Abstract

Buildings are responsible for a significant portion of energy consumption worldwide. Intelligent buildings have been devised as a potential solution, where energy consumption and building use are harmonised. At the heart of the intelligent building is the building energy management system (BEMS), the central platform which manages and coordinates all the building monitoring and control subsystems, such as heating and lighting loads. There is often a disconnect between the BEMS and the building it is installed in, leading to inefficient operation, due to incongruous commissioning of sensors and control systems. In these cases, the BEMS has a lack of knowledge of the building form and function, requiring further complex optimisation, to facilitate efficient all year round operation. Flawed BEMS configurations can then lead to 'sick buildings'. Recently, building energy performance simulation (BEPS) has been viewed as a conceptual solution to assist in efficient building control. Building energy simulation models offer a virtual environment to test many scenarios of BEMS operation strategies and the ability to quickly evaluate their effects on energy consumption and occupant comfort. Challenges include having an accurate building model, but recent advances in building information modelling (BIM) offer the chance to leverage existing building data, which can be translated into a form understood by the building simulator. This study will address these challenges, by developing and integrating a BEMS, with a BIM

for BEPS assisted predictive control, and assessing the outcome and potential of the integration.

Lay Summary

Buildings consume a significant amount of energy worldwide in maintaining comfort for occupants. Building energy management systems (BEMS) are employed to ensure that the energy consumed is used efficiently. However these systems often do not adequately perform in minimising energy use. This is due to a number of reasons, including poor configuration or a lack of information such as being able to anticipate changes in weather conditions. We are now at the stage that building behaviour can be simulated, whereby computer programs can be used to predict building conditions, and therefore enable buildings to use energy more efficiently, when integrated with BEMS. What is required though, is an accurate model of the building which can effectively represent the building processes, for building simulation. Building information modelling (BIM) is a relatively new method of representing building models, however there still remains the issue of data translation between a BIM and simulation model. This thesis explores some of the issues with respect to modelling buildings and the effectiveness of current building simulation tools in prediction for reducing energy consumption.

Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own.

Amar Seeam

July 2015

This work is dedicated to my loving and caring wife Preetila, and daughter Preesha.

Acknowledgements

First and foremost I would like to thank my supervisor, Dave Laurenson. I could not think of a more ideal supervisor. Dave has challenged me to really critically think of my work, and has guided me through the catacombs of PhD research, whilst arming me with the necessary tools, skills and knowledge to navigate along the PhD journey and beyond. He has an unparalleled level of patience and understanding to which I am most grateful for.

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List of Acronyms

ACH	Air Change per Hour
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BACnet	Building Automation and Control Networks
BEMS	Building Energy Management System
BEPS	Building Energy Performance Simulation
BIM	Building Information Modelling/Model
CAD	Computer-aided Drafting
CGI	Common Gateway Interface
DOE-2.2	United States Department of Energy (BEPS tool version 2.2)
EDSL	Environmental Design Solutions Limited (developer of Tas BEPS)
EPBD	Energy Performance of Buildings Directive
ESP-r	Environmental Systems Performance - research (BEPS tool)
FORTRAN	Formula Translating System (programming language)
HTTP	Hypertext Transfer Protocol
HVAC	Heating, Ventilation and Air-Conditioning
IDA-ICE	Indoor Climate and Energy (BEPS tool)
IR	Infrared (a type of radiative heater)
LabVIEW	Laboratory Virtual Instrument Engineering Workbench (system-design platform and development environment)
LBNL	Lawrence Berkeley National Laboratory
MPC	Model Predictive Control
OWFS	One Wire File System
PIR	Passive Infrared (a method of motion sensing)
R-C	Resistance-Capacitance (thermal modelling method)
RRDtool	Round Robin Database tool (data logging and graphing system for time series data)
SAC	Simulation Assisted Control
TCP/IP	Transmission Control Protocol/Internet Protocol
TRNSYS	TRaNsient SYstem Simulation (BEPS tool)

Glossary

Airflow	the movement of air within or between zones.
Boundary Condition	these are the temperature, flux and other environmental conditions that pertain on either side of a surface.
Building Automation	the automatic central control of a building's heating, ventilation and air conditioning, lighting and other subsystems through a Building Energy Management System.
Construction	this refers to a type of wall and its contents which are made of one or more layers of primitive materials. A construction may be opaque or transparent.
Heat Load	amount of heat energy added to a space to maintain a temperature. Unit of measurement is Watt hours
Overheating	when a space is heated above its setpoint.
Plug Computer	compact low power computer encased in a power adapter *plug* form factor.
Radiation	heat transfer where heat energy is transferred via electromagnetic waves.
Scripting	software method to automate the execution of a sequence of tasks.
Setpoint	the desired value in a HVAC system, for regulation of a temperature in a space.
Space	an area in a building (e.g. a room, a portion of a room or a concatenation of several rooms.)
Surface	a surface is a polygon with associated attributes such as emissivity, area, orientation and a specific multilayer construction. Surfaces have two sides, one facing the zone (inside) and the other connected to a boundary condition (another zone, ground, outside). It interacts both radiantly and convectively with its environment. A surface may be opaque or transparent.
Temperature	measurement of heat energy within a Space or a Zone. Unit of measurement used is Celsius.
Zone	can be defined as a 'Space' or in the context of BEPS - a thermal Zone is a simulation unit representing a 'Space' or other building object, equivalent to a Volume of Air, enclosed by 'Surfaces'.

Chapter 1

Introduction

Buildings account for 40% of energy consumption worldwide and 30% of global carbon emissions [Lemmet (2009)]. As the population expands, this statistic is set to rise. A significant amount of the energy required in a building is used to maintain a comfortable environment for the occupants. If the control of that energy is used inefficiently, it can lead to 'sick' buildings.

It is estimated that nearly 90% of buildings unfortunately have inapplicable or ineffective controls [Carbon Trust (2014)], but if they were to be rectified, there could be energy savings up to an additional 20% [CIBSE (2012)]. This is clearly a worrying statistic, and if it is addressed there is great potential to save significant amounts of energy worldwide.

'Smart' or intelligent buildings have emerged to provide solutions to energy efficiency and comfort problems by utilising information and computer technology. They employ building energy management systems (BEMS), which are dedicated systems installed to manage a building and energy consumption, whilst maximising comfort for occupants.

However, current BEMS are not as dynamic as they could be, and even in real world use, are often neither correctly used, nor optimised for energy efficiency. Changes in the environment (both internal and external) can affect the operation, and over time settings drift to inefficient boundaries, leading to situations that make occupants uncomfortable and a waste of energy.

Model predictive control (MPC) [Cumali (1988)] is seen as one particular solution to this problem, whereby a model of the building's thermodynamic behaviour and response is created, using inverse data driven modelling techniques, from limited building knowledge. MPC models are often used to represent a building's plant (e.g.HVAC), in terms of temperature regulation, rather than modelling a whole building and other associated physical processes (such as airflow). They can be used to predict conditions to make better decisions regarding the control of that plant and its subsystems in order to save energy and provide optimum levels of comfort in anticipation of increased occupancy or changes in the weather. This predictive approach to control can ensure that the building environment is at an optimum level for the occupants, and energy is used frugally.

Simulation assisted control (SAC) [Clarke (2001)] is a more recent alternative and variation of MPC. Whereas MPC requires a period of training and data collection over a certain period of time in order to create a plant model using black or grey box techniques, SAC utilises pre-existing (i.e. white-box) building models, which fully represent the building in terms of their geometry, operations and constructions and can have their energy performance and thermodynamic and airflow behaviour predicted using building energy performance simulation (BEPS) tools, such as ESP-r. These predictions can then be used to formulate energy efficient control strategies, such as *optimum heat start up*, taking full consideration of all potential physical processes in a building, and are not constrained by the range of experience learned by MPC techniques from training data, which would otherwise only consider a subset of the building's true energy performance.

Building information modelling (BIM) is an emerging discipline which can potentially aid in providing the required information needed to create BEPS models. Essentially BIM is an extension of 3D CAD, with supplementary building specific information, though they require further translation in order to represent the additional nuances required in BEPS models, such as the processing of architectural geometry into thermal boundaries and zones. A lack of information or approximation of the geometry or constructions may require calibration to a set of data to address uncertainty (therefore equivalent to a grey box model, which assumes some level of knowledge).

BIMs have been proposed to be implemented in BEMS, but so far only in facilities management use cases, where the BIM is linked to various sensors, allowing visualisation in 3D user interfaces. Consequently, the rich information which can be readily available in BIMs, make them especially useful to be extracted for BEPS, where the building behaviour can be simulated and predicted in the control core of the BEMS, to generate energy efficient controls strategies, and thus enable buildings that are better managed.

Converting BIMs to be used in BEPS tools currently requires a degree of human intervention during the translation (i.e. semi-automated), due to the intricacy required in assigning BEPS specific details. If the process is automated without human intervention, an approximate model may be produced, which may require further calibration with measured data to tune the model and *'fill the gaps'* with BEPS specific details not contained in the original BIM. These approximations may create various levels of uncertainty that lead to a model that is further divergent from reality, but may appear plausible in some cases, if not fully investigated. Furthermore, there is the issue of quality of data in terms of information provided to create the building model. That is, calibration can be used as a means to reduce uncertainty, when faced with a lack of information, which can rectify the model according to the data provided, but may be limited in scope and application since there may be a dependency on the measured data. In other words, calibration may not be the best approach when creating models, particularly if detailed data can be attained.

1.1 Motivation

As part of the study, the author collaborated with a modular construction company, Enemetric (formerly Powerwall Space Frame Systems), to design and develop an affordable BEMS that could be installed at the off-site factory stages of construction. During the period of the study, the company were exploring automation in computer aided design of buildings and how to make their buildings more *intelligent*. This stimulated a further exploration into building modelling theory and the use of simulation. It was soon found out that there was scope to implement BIM with BEMS and integrate with simulation assisted control logic, and that it was an area which has had little investigation since the technologies have only recently benefited from further advances in computing technology.

1.1.1 The Focus

It was decided that the focus should be in the efficient use of heating for residential houses in the UK, since household heat demand has risen over the past 40 years from 400 TWh/y to 450 TWh/y, despite a marked improvement in the energy efficiency of homes and a slight reduction in the severity of winters, whilst also taking into account nearly half (46%) of the final energy consumed in the UK is used to provide heat. Furthermore, there is a government goal to significantly reduce carbon emissions (by 80% by 2050 relative to a 1990 baseline) [DECC (2012)].

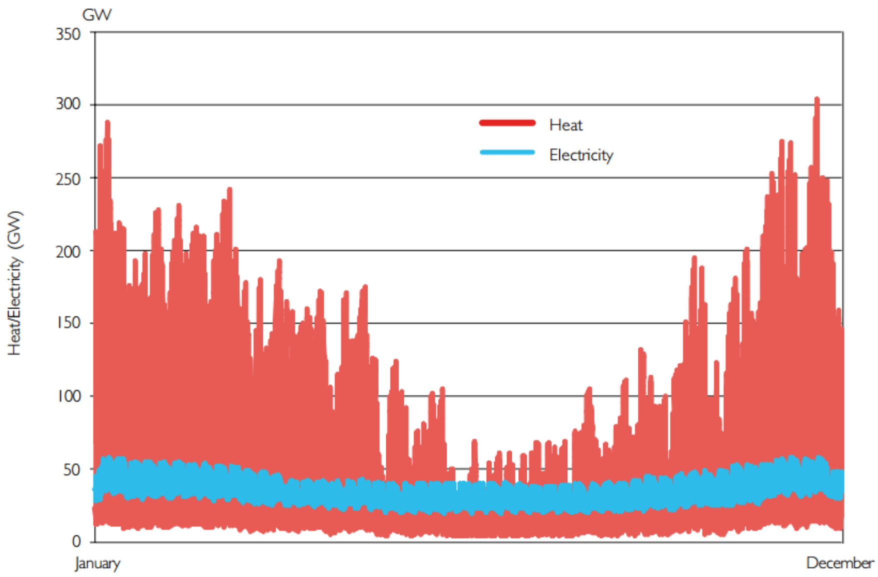

Figure 1.1: Comparison of heat and electricity demand variability across a year (domestic and commercial) for year 2010 from [DECC (2012)].

As heat demand varies considerably across the year, compared to electricity (Figure 1.1), this makes it challenging to simulate and benchmark models in terms of heat energy use, since metrics used to determine goodness of fit between measured and simulated data tend to only consider electricity consumption. With the emergence of smarter heating controls which can vary heat delivery between rooms, this can become especially more challenging to measure and compare, since the majority of heating comes from gas-fired boilers, making it difficult to disaggregate. Smarter heating controls however allow individual room heating, so energy can be saved from not heating unoccupied rooms. Though heat from electricity makes up less than 10% overall heat energy used (in the UK), it was decided that an electric heating system would be used, since it would be simpler to monitor and zone into individual rooms and control. With that being said, the electrification of space and water heating has also recently started to gain traction as a strong option for achieving a low carbon buildings sector [Munuera *et al.* (2013)].

1.1.2 Test Building

A demonstrator house was provided by Enemetric to develop and install a BEMS with a zoned electric heating system and create a building model of, to simulate predictive control strategies. Essentially the house was used as a test bed to trial various technologies, including different kinds of sensor and actuators, which would be able to provide suitable measurement data such as the average heating consumption shown in Figure 1.2 and solar gains shown in Figure A.3 for validating the building model created, and thus evaluate predictive control capabilities, and the integration of BIM, with BEPS and BEMS as a concept.

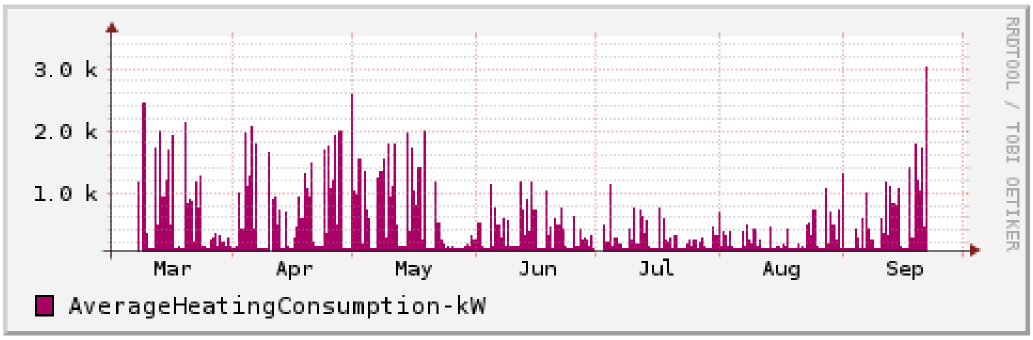

Figure 1.2: BEMS Measured Average Heating Consumption

1.2 Hypothesis

This thesis argues that detailed building models are more desirable than those that require extensive calibration, and that BIM adoption should be encouraged to enable the integration of BEPS in BEMS for predictive heating control applications.

1.3 Contributions

1. The primary contribution in this thesis is the demonstration that approximated building models should be avoided in BEPS-BEMS integration and that calibrated models are no substitutes for models with detailed building knowledge, when applied to predictive building control applications. As such, this thesis highlights the importance of adopting BIM technology, so that it is not only used to enhance monitoring applications, but also predictive control.

2. This thesis looks at a SAC application for a residential house, and considers the whole house dynamics, using zoned electrical heating. Most SAC applications have focused on larger buildings or test beds presenting a subset of the building.

3. A BIM was created, with varying levels of uncertainty, and evaluated in BEPS for goodness of fit using automated calibration and validation techniques and finally retrospectively tested for a BEMS simulation assisted control strategy. In terms of control strategies, the BEMS developed for the demonstrator house provided scheduled heating control from electrically monitored radiators. This enabled heated rooms to have their heat energy measured (using electricity monitoring) and compared against the building simulator. To the best of the author's knowledge, this is first time this has been attempted.

4. The simulator used in this study was ESP-r. Since a full model was created based on a monitored house, which could have measured data

compared with simulated model data, this thesis also represents a validation case for ESP-r and its prediction capabilities.

5. The study further investigates the effects that solar gains have in a residential house with electrical zoned room heating, as part of the validation.

6. A BEMS platform was developed specifically for this study, including the monitoring, control and automations systems. ESP-r was integrated into this platform, and as such the complete platform can be used as a simulation assisted controlled BEMS.

1.4 Organisation of Thesis

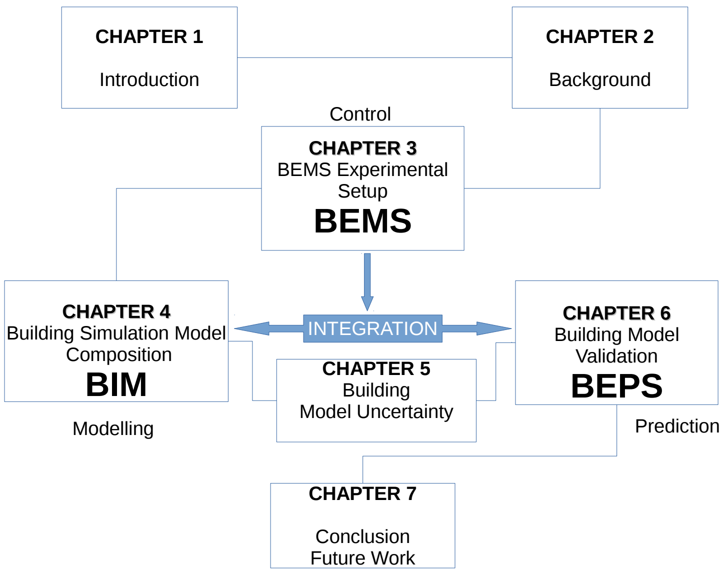

Figure 1.3: Thesis Layout

Figure 1.3 visually depicts the organisation of the thesis. The central theme is the integration of BEMS (Chapter 2) with BIM (Chapter 4), implemented in BEPS (Chapter 6) for predictive control using building simulation models.

The detailed overview of the thesis is as follows :

Chapter 2 reviews the background to predictive control and contrasts the differences between model predictive control and simulation assisted control in terms of black, grey and white box modelling techniques in the context of building energy management systems, whilst introducing the reader to building information modelling and highlighting its importance as a mechanism for providing detailed building specific data for simulation.

Chapter 3 covers the BEMS experimental setup. Here the development of the BEMS is presented, including descriptions of the:

- BEMS platform development
- communication systems
- data acquisition (monitoring)
- user interfaces
- sensors and actuators
- control and automation

Chapter 4 explores the creation of the building model in ESP-r, and decomposes its data structure into various components representing the:

- building geometry (zones)
- constructions (materials)
- operations (control)
- airflow

A zoning strategy to divide the building model into respective zones is discussed, and a detailed description of each zone and their relationships is given.

Chapter 5 looks at building model uncertainty, by approximating the model presented in Chapter 4, and introduces goodness of fit metrics used to judge a model's prediction quality. These metrics are then minimised during an attempt at automated calibration. It is further discussed whether these metrics are fit for purpose according to the current guidelines widely used in building calibration and validation studies.

Chapter 6 presents the results of validating the full building model, with a minor calibration to ascertain one unknown value for insulation density. Two datasets are used for the validation, and the goodness of fit between measured and simulated data is computed in terms of temperature and energy response for individual zones in the model. Once the model's validation has been discussed, the use case for optimum heat start up as an example of simulation assisted control is retrospectively evaluated.

Chapter 7 concludes the thesis, and discusses further work.

Chapter 2

Background

2.1 Introduction

With 40% of energy consumed in buildings, the Energy Performance of Buildings Directive (EPBD) has been recently introduced in the European Union. The principal objective of the EPBD is to promote the improvement of the energy performance of buildings within the EU through cost-effective measures. In 2010, the EPBD Recast (Directive 2010/31/EU) was initiated [EU (2010)]. The EPBD recast Article 9 requires that *"Member States shall ensure that by 31 December 2020 all new buildings are nearly zero-energy buildings; and after 31 December 2018, new buildings occupied and owned by public authorities are nearly zero-energy buildings"*.

Furthermore, by 2020, the European Community [EU (2015)] wants to:

1. Use 20% less energy versus the reference year of 1990.

2. Emit 20% less greenhouse gases versus the reference year of 1990.

3. Achieve 20% of overall energy consumption from renewable forms of energy.

For the UK, the target energy performance of buildings is set in the Part L of the Building Regulations, which was revised in 2013 [GOVUK (2013)], and enforced in April 2014. This Part L revision has now increased the performance targets so that new homes should achieve zero-carbon performance by 2016, and non-domestic buildings later in 2019.

Nearly half of the UK's greenhouse gas emissions are from the energy used to generate heat [GOVUK (2014)], and the vast majority of homes rely on fossil fuel powered gas boilers, and inefficient heating systems.

The UK government has recognised a great opportunity to reduce carbon emissions by replacing these inefficient systems, and improve insulation, as part of a Carbon Plan [GOVUK (2011)].

Much has been done to improve insulation characteristics of houses, with millions of homes having insulation upgraded (cavity walls and loft) over the past couple of years [CBI (2009)]. However there has been a lack of research to address heating systems, in terms of improving control strategies, though there has been a growing trend in internet connected 'smart' heating control devices that give occupants more options for control and 'learn' how they use it. These do little more than guess schedules such as the Nest Learning Thermostat, after a period of learning how occupants set temperatures throughout the day. Other examples of smart heating control devices, include the Tado which guesses arrival times based on GPS coordinates, and the British Gas Hive system. These systems rely on understanding human behaviour in an attempt to better control heating beyond predefined rules, which are commonly used to schedule heating. In larger buildings, building energy management systems

(BEMS) face the same problem, but on a greater scale due to the size and complexity of heating, ventilation, and air conditioning (HVAC) systems. BEMS are often programmed with static rule based schedules, which are not optimised to react to changes in a building's use, which can often be dynamic.

A better method would be to employ a predictive control strategy that can supersede traditional rules based systems. There are two main techniques for predictive control in buildings that are currently being researched to improve control in building energy management systems. These are model predictive control (MPC) and simulation assisted control (SAC). Both techniques, rely on being able to accurately forecast conditions based on various environmental factors, though can differ in their approaches, and some literature [Sakellariou (2011), Henze (2003), Henze and May-Ostendorp (2012)] occasionally describe them as being essentially the same due to the fact they both use models for prediction. Mahdavi was one the first proponents of SAC identifying it as a separate method altogether, claiming *'This concept, which should not be confused with model-predictive control, involves the incorporation of explicit numeric performance simulation in the control core of buildings' environmental systems'* [Mahdavi (2013)].

There is also a key difference in the type of models used in MPC and SAC. The majority of the literature on MPC deal with developing detailed models [Ruano *et al.* (2006), Široký *et al.* (2011), Ferreira *et al.* (2012), Bueno *et al.* (2012), Lehmann *et al.* (2013), Royer *et al.* (2014)], starting with limited or no knowledge of the building, and tend to focus on one particular application to optimise, which often are HVAC systems. SAC takes a whole building approach, requiring a full model to be developed from a building information model (BIM) or 3D CAD model, and can calculate a wide range of physical interactions using a pre-validated building energy performance simulation (BEPS) engine. Examples of well-known BEPS software include EnergyPlus and ESP-r. MPC requires modelling of the building derived from first order principles or system identification. This requires model training; for example neural networks can be used for this purpose for black box models. Once the model is trained, it is a simplified, though highly focused, representation of the building control systems, rather than a representation of the complete building. The introduction of another parameter into the model would require further retraining. On the other hand SAC utilises a full building model, allowing more diverse use cases to be applied and other control strategies to be explored, without having to go through a process of training and data collection for model verification. A lack of information in a building model may require model calibration to fit parameters, similarly to the MPC method, however this may lead to an incorrect physical model representation. For the case of smaller buildings, such as houses, the knowledge-based SAC approach can be viewed as more desirable, as they do not have complex HVAC systems, that MPC data-driven methods often seek to optimise. Examples of approaches which are highly focused on optimum HVAC control, were performed by Sierra *et al.* (2007), Liu *et al.* (2014) and Cumali (1988). There is as yet no studies for SAC in smaller buildings such as houses, which this thesis intends to address.

2.2 Building Energy Management Systems (BEMS)

Building energy management systems (BEMS) are computer-based systems that manage, control and monitors of building services such as HVAC, lighting and security and the energy consumption of various service components in a building.

Typical BEMS Functions are shown in Table 2.1. The HVAC system is controlled by combining control laws between sensors and actuators. A simple

Table 2.1: BEMS Functions

Functions	Sensors	Actuators
HVAC	Temperature, Humidity, Carbon Dioxide	Valves
Lighting	Light, PIR	Luminaires
Energy Monitoring	Current Transformer	Load Control
Safety	Carbon Monoxide, Smoke	Alarm, Siren
Security	Camera, PIR	Alarm, Siren

control strategy would be to actuate a valve that turns a heating device on, until a temperature sensor reaches a desired target temperature (called a setpoint.) Moreover, this control strategy will be maintained by a static schedule such as the one shown in Figure 2.1.

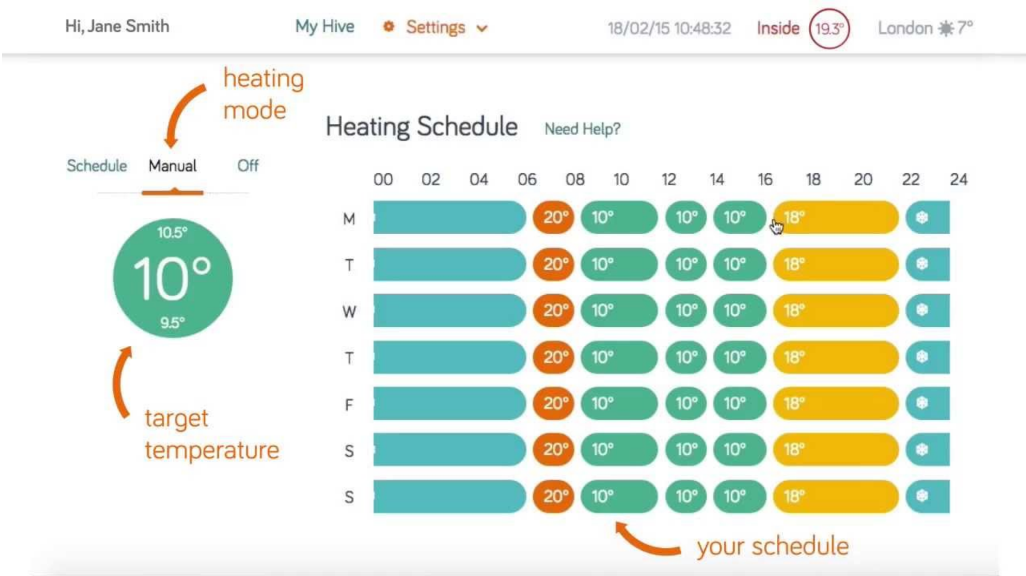

Figure 2.1: British Hive Heating Schedule

The schedule shown in this figure, presents the times for setpoints throughout the day in a house. For instance from 6am to 8am the heating system setpoint is set at 20°C, which is a morning heat phase. This would appear a reasonable strategy for people waking up in the morning, and getting ready for the day.

From 10am to 4pm (16 hours) the setpoint is 10°C, essentially deactivating the heating during this period, which can be assumed to be an unoccupied period. However the later schedule from 4pm (16 hours) to 10pm (22 hours) is set to 18°C. If we assume the house is not occupied until 6pm, this is an inefficient strategy, leading to a unoccupied house being heated for two hours, wasting energy. An improved method would be to predict the switch on time to enable the heating so that the setpoint is reached exactly at the time of arrival. For this to be achieved the control core requires to be modified to perform prediction using model based techniques. In this scenario, if the house is to be occupied at 6pm, the predictive controller would calculate the start up time (which could be later than the scheduled 4pm time), based on weather forecasting and modelling of the house thermodynamics. In Chapter 4, an example of this optimisation will be explored.

2.3 Model Predictive Control (MPC)

Model predictive control [Qin and Badgwell (2003)] is an advanced technique that can be used to represent the dynamic behaviour of constrained systems, and predict control inputs and plant responses. MPC originated as a method of improving control in industrial automation applications such as those found in process and petrochemical industries. Nowadays MPC techniques can be found in other application areas including food processing, automotive and aerospace applications.

Recently, MPC has been seen as a solution to improve control in BEMS, though is still relatively uncommon, compared to other applications. This has largely been due to high computational requirements that are only now being able to be met.

Generally, MPC takes a data driven approach to model creation. Using this approach, a mathematical representation of the building can be created, as opposed to a physical representation, based on a building information model. Therefore MPC requires real measured data to determine the model structure and parameters. Furthermore, on-site measurements must be carried out for a certain period of time, in order to capture events that can fully represent the dynamic behaviour in a building. The amount of data required in terms of measurements and building geometry specifics was analysed by Foucquier *et al.* (2013), who contrasted various methods to building modelling, and categorised them as either black, grey or white box techniques, as shown in Table 2.2.

Table 2.2: Building Modelling Techniques (Foucquier *et al.* (2013))

Methods	**Building Geometry**	**Training Data**	**Physical Interpretation**
Physical or *white box* method	A detailed description of the building geometry is required	No training data are required	Results can be interpreted in physical terms
Statistical or *black box* method	A detailed description of the geometry is not required	A large amount of training data collected over an exhaustive period of time is required	There are several difficulties to interpret results in physical terms
Hybrid or *grey box* method	A rough description of the building geometry is enough	A small amount of training data collected over a short period of time is required	Results can be interpreted in physical terms

2.3.1 Black-Box Modelling

A black box is a mathematical model that is constructed from analysing measured observed data, and assumes no prior knowledge of the system. Essentially the black box represents a system with observable inputs and outputs, requiring the 'contents' of the box to be derived. The contents in this context is a non-physical representation of the system, or model parameters, therefore building geometry is not required to be known. These parameters can be identified using statistical methods such as a regression analysis between the outputs (i.e. measured room temperature) and inputs into the system (i.e. temperature setpoint). Machine learning techniques, such as neural networks are often employed to perform the analysis.

Typically, a separate model or black box will be created for each room (thermal zone) in a building or parameter of interest.

An example of the black box model from Royer *et al.* (2014) is shown in Figure 2.2.

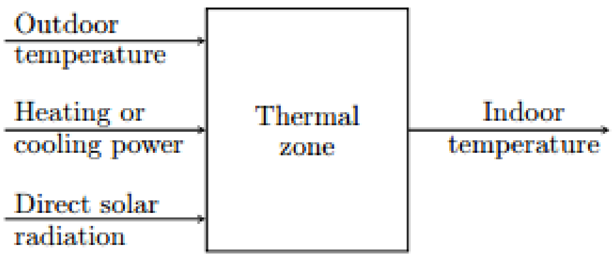

Figure 2.2: Black box model of three inputs/one output representing a thermal zone (Royer *et al.* (2014))

Here the main signals influencing indoor temperature are outdoor temperature, direct normal solar radiation and heating/cooling power. In Royer *et al.* (2014), they used BEPS software EnergyPlus and Matlab to estimate the model parameters, and achieved a high percentage of fit (77%) between validation data and model output.

Neural networks can well approximate the complex relationship between the system inputs and the inside air temperature, using measured data or BEPS, though Herzog *et al.* (2013) concluded neural networks deliver results of low quality, if the training period varies from the test period. This became apparent when they performed a comparison of neural network based models with BEPS based models, though recognised that the principal advantage of neural network based models was their flexibility and that they required hardly any information about the building and its building services to reproduce the thermal behaviour.

Most MPC black box applications in buildings focus on HVAC optimisation. For example, Ruano *et al.* (2006) used neural networks for prediction of the building's temperature to control air conditioning units and achieved better results than an equivalent building physical model, but it required one month of training data for a summer period. Ferreira *et al.* (2012) applied neural networks for HVAC control in public buildings for both winter and summer periods and attained nearly 50% in energy savings compared to conventional control.

2.3.2 Grey-Box Modelling

The grey-box approach assumes some prior knowledge, though requires less measured data. In many studies that use this approach, the lumped parameter method is employed which decomposes building thermodynamics as a network analogue to electrical circuits. In this analogy, a thermal resistance (R) is analogous to an electrical resistance, and thermal capacitance (C) is analogous to an electrical capacitance, with various energy inputs introduced from gains to the network (occupancy, solar) and heating (or cooling) input. This is also known as the RC (Resistance-Capacitance) method, and has seen various applications in MPC.

Thermal capacities and resistances are initially determined from construction plan data, and materials used. BEPS or measured data can be used to tune the parameters.

In one of the recent implementations of RC-based MPC, Široký *et al.* (2011) saved up to 30% energy when it was applied to a building heating system. Figure 2.3 shows an example of the RC modelling principle they applied. It is based on the description of heat transmission between nodes that are representing temperatures. In this example from Široký *et al.* (2011) there are two rooms where, ϑR1 and ϑR2 are the temperatures in the room R1 and R2, respectively, ϑ0 is the outside temperature, ϑSW is the temperature of the supply water used for floor heating, CR1 denotes the thermal capacity of the room R1. Resistances represent the thermal resistances between the nodes. This node based approach is a popular method to modelling buildings, particularly for temperature simulation.

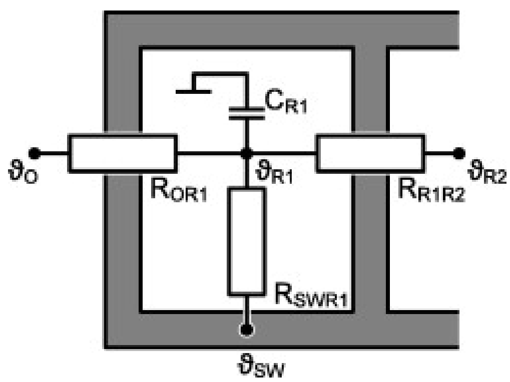

Figure 2.3: RC modelling, based on the description of heat transmission between nodes that are representing temperatures (Široký *et al.* (2011))

Lehmann *et al.* (2013) used a complex RC approach for MPC in integrated room automation for control of ventilation, blinds, heating and cooling as part of the OptiControl project.

In the OptiControl project, due to a number of approximations and assumptions made regarding solar radiation through windows, and heat transfer through walls, building simulation software TRNSYS was used to assess the effect of simplifications made. They determined that the deviations were small enough that their 12th-order RC-model allowed for a realistic representation of the investigated building zones' thermal dynamics.

Though most RC-based approaches investigate and focus on phenomena in buildings, Bueno *et al.* (2012) developed a resistance-capacitance network model for the analysis of the interactions between the energy performance of buildings and the urban climate, to determine the dominant mechanism by which indoor environments affect outdoor air temperatures. They concluded that waste heat emissions from HVAC systems were the main mechanism by which energy performance of buildings influenced outdoor thermal conditions.

Not all grey box methods are based on lumped parameter RC models. For example, Sterling *et al.* (2014) contrasted a black box method (artificial neural networks) with a grey box method. In this example, the grey box method also employed an artificial neural network, but with parameters tuned using a building simulator (EnergyPlus), rather than using measured data which was only used in the black box method. They concluded that both methods still required a full year covering all seasons for training data.

Using either black box or grey box methods requires a subtle balance between measured data and existing building information to achieve comparable results to BEPS based models. Not only that, the majority of MPC based studies that use these methods often utilise BEPS to help aid model verification. It can be therefore said, that since there appears to be a reliance on BEPS in these methods, BEPS should be used directly, when there is a sufficient amount of building information available. In particular, BEPS based SAC should require less or no measured data to perform adequate prediction, since BEPS tools have already been validated. Furthermore, a BEPS model should require little to no calibration, if there is a sufficient amount of building knowledge in terms of building geometry, construction and building control characteristics.

2.4 Simulation Assisted Control

Whereas MPC techniques use the black or grey box method, simulation assisted control takes the white box method or physical model approach and requires a full building model and a validated building simulator such as ESP-r.

Building simulation software is increasingly being employed by architects and facilities managers to model performance of a building and energy use. Recent developments in building information modelling (BIM) look to integrate CAD software with energy performance tools to aid design of energy efficient buildings.

Using this software, the building can essentially be prototyped virtually, and various profiles of use can be applied, in order to make control and design decisions. It is said that decisions made early in the building design process, based on simulation results, can have a substantial impact on the building performance [Hemsath (2013)].

Building simulation software permit a wide range of physical attributes to be applied in a building model and analysed, such as thermal loads (e.g. TRNSYS) and lighting luminance (e.g. Radiance).

The building model, in the context of building simulation is an extension of the geometric model, which is supplemented with information concerned with energy balance characteristics, such as insulation parameters for thermal modelling or renewable energy sources for electrical load modelling.

Energy gains in a building are from lighting, equipment, occupancy, windows (solar radiation) and heating. Losses are generally transmitted through windows, walls, ceilings, floors, roofs, doors, infiltration and ventilation (Figure 2.4). These are all parametric inputs in a building simulator.

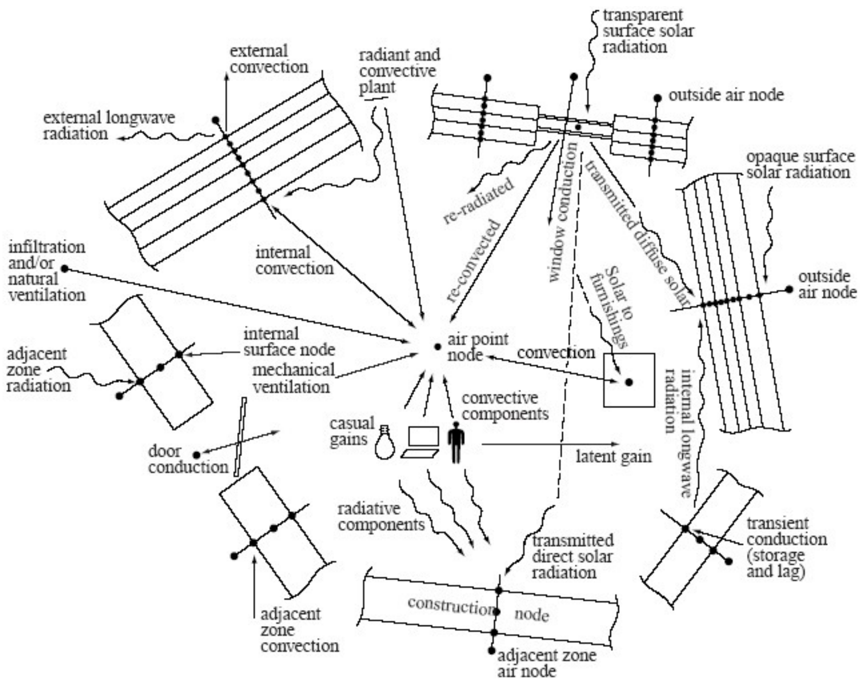

Figure 2.4: Building Energy Flow Paths (from Clarke (2001))

Building simulators can be used to test out various occupancy profiles and usage scenarios that could occur in building, with respect to energy use and balances. They contain calculation engines based on validated building physics solvers. In terms of energy balances, there will generally be loads and gains from heating and cooling of the building due to climate and building services acting on the building environment, and internal gains from people and equipment.

Simulator software such as ESP-r, allows exploration of the complex relationships between building parameters for form, fabric, airflow, plant and control [Strachan *et al.* (2008)]. ESP-r is based on a finite volume, conservation approach whereby problems are transformed into a set of conservation equations that are then solved at successive time-steps in response to climate, occupant and control system inputs. Other software take various approaches to solving building physics problems. ESP-r is notable in that it is an *integrated* solution, where it not only considers thermal domains, normally only considered by the aforementioned black and grey box methods, but also airflow. TRNSYS for example only performs thermal simulation. The coupling of the two domains, and the intricacies of inter and intra zone air flow are significant areas of research [Beausoleil-Morrison (2000)], and can enable the exploration of complex interactions. This would be difficult to achieve using black box or grey box methods, that often only represent a subset of the building knowledge, whereas BEPS white box models take a whole building approach. The key difference is that BEPS tools such as ESP-r have been extensively validated for numerous test cases. ESP-r itself has been subject to many empirical validation studies dating as far back as 1978, and has strong roots as a research oriented tool, with the first study [Clarke and Forrest (1978)] comparing the simulator's response against monitored Scottish bedroom houses in Livingston. Since then, the software has seen sustained development and has been incrementally improved, with components gradually added to assist the integration of building dynamics to simulate the real world as much as possible, particularly as part of numerous PhD theses [Strachan (2000)].

Though the black or grey box method for MPC requires less building specific data, there is a greater reliance on measured data, which requires the building to be constructed and fully operational for a certain period of time (Sterling *et al.* (2014) concluded up to at least a year). Clarke *et al.* (2002) said *"Even the best trained self-learning controller cannot extrapolate beyond its range of experience"*, and presented simulation assisted control in building energy management systems as one of the first applications of SAC. Clarke *et al.* (2002) explained that there were inherent limitations in the black-box approach as the controller has no knowledge of the cause and effect relationships between the elements of the controlled system and external excitations, such as climate and occupant interaction. In particular they presented the following benefits of SAC over MPC methods:

1. They are able to address cause and effect scenarios.
2. They can adapt to the impact of changing building use or operation (provided that the change is incorporated into the model).
3. They potentially offer better control through calculation of interactions and can identify the factors that result in particular building performance.
4. They provide the possibility of comparing options for different control strategies by testing them on the building model.

In Clarke *et al.* (2002), a prototype control structure was developed and tested in an environmental test room operated by Honeywell at Newhouse in Scotland. This environmental test facility consisted of two realistically dimensioned rooms surrounded by temperature controlled voids. The constructions used in the test rooms were similar to those in a real dwelling (insulated cavity walls with double-glazed windows) and each room was heated by low temperature radiators supplied from a central boiler. In this study the predictive controller was set to optimum start up mode.

They successfully demonstrated predictive heating start up to reach a desired target temperature by a specified time, by integrating ESP-r building simulation software with a LabVIEW based BEMS. Though a successful demonstration, they concluded that further focus was required on a full-scale real building subject to external climate variation.

Maitos *et al.* (2010) also investigated SAC using ESP-r by developing a prototype BEMs (KOBRA) and new subroutines to link ESP-r into the BEMS. Experiments were carried out in a single zone purpose built test chamber. Data collection (monitoring) for temperature was performed by standalone HOBO dataloggers, and KOBRA was used for control. This study also did not consider the effects of external climate, or whole building simulation. Other examples of ESP-r integration include that with Matlab to replace the FORTRAN control system, using TCP/IP communication to link them [Yahiaoui *et al.* (2005)]. The notable focus in this study was the use networking to run simulations on separate computer hosts (which could be geographically separated). This is otherwise known in the field as 'co-simulation', where another calculation engine (in this case - *Matlab*) is integrated with a BEPS. Co-simulation does not necessarily require networked communications to link software, and another example of this integration was carried out by Pichler *et al.* (2011), who investigated cooling strategies using TRNSYS with Matlab, on a single computer host.

The integration of ESP-r with BEMS, has mainly focused on heating control but Mahdavi, who first proposed SAC, has led the way in combined heating, lighting, shading and ventilation simulated assisted implementations [Mahdavi *et al.* (2009b), Mahdavi *et al.* (2009a), Chang and Mahdavi (2001)].

In Mahdavi *et al.* (2009b), simulation assisted control of a BACnet system using Radiance for lighting simulation and Matlab for thermal simulation was demonstrated, claiming *"existing thermal simulation engines are difficult to interface with programmatically"*. Taking this into consideration, the author believes that ESP-r is a very flexible BEPS tool that can be interfaced to easily for thermal simulation, when using a Unix/Linux based environment for scripting. This will be demonstrated later in this thesis, by scripting ESP-r to evaluate simulation assisted control. Their simulation assisted control method was implemented for lighting, shading, ventilation and heating domains. Various options to be simulated included states for shading devices, luminaires, dampers and radiant heating devices. Prediction results are compared and evaluated against previous settings by building users and operators, with the top ranked control state subsequently implemented, leading to a set of respective commands sent to a BACnet gateway for execution. Only lighting and shading states required to be executed, since the thermal simulator determined that the outdoor temperature was predicted to be high enough to negate the need for indoor heating. A rule based scheduled system would not have been able to anticipate this behaviour, so the benefits of predictive/simulation assisted control can be clearly seen.

In Mahdavi *et al.* (2009a), simulation assisted control of window positions in two reference buildings was investigated. The idea was to utilise the day-night difference in outdoor air temperature toward passive space cooling via optimized dynamic operation of windows. Mean overheating (of the indoor air in selected spaces) was used as the relevant performance indicator. They used the EDSL Tas BEPS software tool to dynamically simulate the thermal performance of buildings and their systems. This particular application solves the sensible heat balance for a zone by setting up equations representing the individual energy balances for the air and each of the surrounding surfaces. These equations are then combined with further equations representing the energy balances at the external surfaces, and the whole equation set is solved simultaneously to generate air temperatures, surface temperatures and room loads. To determine the validity of their system, they examined deviating weather forecasts (by overestimating and underestimating temperature and solar data) , and the system's method of control ranking options similarly used in Mahdavi *et al.* (2009b) remained valid.

Zhou and Park (2012) identified that optimising temperature schedules saves the most energy in an office building when applying simulation assisted control using DOE-2.2. They noted that this was a challenge because there is no available function in the DOE-2.2 software to simulate the energy management and control system. They investigated various temperature schedules that were closely aligned to thermal comfort in office buildings, and human work productivity, for example temperature set back when occupancy rates dropped, and lowering the temperature setpoint in the morning until occupancy body temperatures reached a certain comfort level. By applying these simulation assisted control strategies they demonstrated a 2.25% energy reduction, noting that though the gain was minor, the target building was modern and had good levels of insulation, glazing and an efficient HVAC system.

This study intends to address previous issues not dealt with in the existing SAC literature. For example Clarke (2001) had not considered full scale building operation and external climate with ESP-r. This thesis specifically looks at external climate variation with ESP-r. Mahdavi's previous studies are more focussed on lighting, ventilation and cooling, whereas in this study the focus is predominantly on heating. Finally, Zhou's implementation of SAC did not use a full building model and used DOE-2.2 which does not simulate the energy management and control system, whereas ESP-r has this capability.

The challenge in simulation assisted control however is having an accurate model and representation of the building. Capturing the right level of data is now possible with the advent of BIM technology. However there are additional steps required to accurately match the simulation model details such as the thermal characteristics, which are often not stored as part of the architectural geometric data. Calibration may be used if these characteristics are not available, to determine unknown parameters. However building model calibration is not a trivial problem, as energy models are complex with many interactions [Clarke (2001)]. In the area of building simulation research, it is still a deep and challenging problem, largely dependent on the quality of measured data available [Li *et al.* (2013)]. In this thesis it will be demonstrated that having as much source data as possible, to create a building model, is highly desirable when using a validated BEPS tool such as ESP-r, and that calibration is no substitute for a highly detailed model, with accurate construction data. With this in mind, BIM becomes an attractive solution as a source for building simulation model creation, since BIMs already contain a wealth of highly detailed and relevant building related information that goes beyond what is traditionally available in a 3D CAD model.

2.5 Building Information Modelling (BIM)

BIM is a relatively new and exciting paradigm in the construction industry, and is a method of generating and managing building data using software. Information about a building is held in a central repository. BIM evolved as a superset of the 3D CAD model of a building, containing parametric information supplemented with object relationships, which can support the simulation of a building virtually, permitting experimentation, by modification of design parameters.

The majority of information for BEPS models is captured during the design phases in BIMs, and new buildings are now required to adopt the technology [GOVUK (2012)].

BIM already identifies building elements (walls, slabs, windows, doors, and stairs) by their attributes (functions, structures, usage, and others) using parametric technology, and it reflects any changes in the building elements immediately into the building configuration information by recognising the relations between those attributes [Song *et al.* (2012)]. This makes it ideal for BEPS models which require precisely this kind of information and detail and therefore BIM driven SAC is an exciting proposition. Furthermore, Katranuschkov *et al.* (2011) emphasised that one of the main gaps that exist in current practice of BIM and energy analysis was the insufficient use of simulation (based on BIM) and monitoring (based on installed sensors in the BEM) during the whole life cycle.

However there still remain issues with BIM translation to BEPS models, when extracting the relevant information for simulation. This had led to several initiatives to address methods of translation. One example is Geometry Simplification Tool (GST), developed by The Lawrence Berkeley National Laboratory (LBNL) in conjunction with Graphisoft [O'Donnell (2014)]. It was recognised that there are four primary benefits for the approach they developed:

1. Reduce the amount of time and cost required to develop a whole building energy simulation model.
2. Enable rapid generation of design alternatives.
3. Improve the accuracy of BEPS.
4. Result in significantly better performing buildings, with significantly lower energy consumption than those created using the traditional design process, *especially if the simulation model was used as a predictive benchmark during operation*.

The final benefit is a clear statement of the potential for BIM to be used in a SAC-BEMS application. Furthermore a well developed BIM when used in a predictive control application should not require any training period or little calibration, when there is a sufficient amount of detail and information available. Essentially this means, if there is seamless translation from a BIM to BEPS model, predictive SAC in BEMS can potentially become a reality from the building's first day of operation. This is now becoming possible, since all new buildings require BIMs when they are being designed and constructed, therefore negating the need for black box and grey box methods. Further work is needed however to ensure that BIMs have sufficient information to allow SAC to work - this can be accomplished by integrating more BEPS specific details, which are currently not present.

2.6 Summary

In this chapter, predictive techniques using various building models for BEMS have been discussed as a method to improve control, by anticipating conditions that rule-based scheduled systems cannot. Various modelling methods have been presented, in terms of model composition, contrasting black and grey (MPC basis) and white box (SAC basis) methods, noting that BEPS covers multiple calculation domains (thermal and airflow). It has been concluded that even though the benefits of using BEPS for predictive control are clear, there is a lack of research in SAC applications. It is also noted that a further investigation using simulation based control techniques and SAC-BEMS integration is required (at least for new buildings), since BIMs are becoming a more popular (and in fact mandated) method of storing and maintaining building information.

Chapter 3

BEMS Experimental Setup

3.1 Introduction

This chapter will discuss the experimental setup, and features of the BEMS, namely, the monitoring, control and automation functions.

To evaluate simulation assisted control requires several components.

(1) A building model (BIM).

(2) A building energy management system (BEMS).

(3) A building energy performance simulator (BEPS).

(4) A test building.

For (1) and (3), ESP-r has been used to create the model, and perform simulation for prediction. For (2), a BEMS has been designed, developed and integrated into the test building (4), as opposed to using an existing solution

(This was part of a KTP partnership requirement to create a system specifically for Enemetric and demonstrate its potential as a modular building solution).

3.2 BEMS Components

The various layers to the system are as follows.

1. A monitoring layer which records sensor values from the environment, and measures and logs energy consumption.
2. A control layer which provides interfaces to allow user interaction with actuators (e.g. changing temperature of a room using 'setpoints').
3. An automation layer which acts upon various user rules set in the system (e.g. heating schedules).
4. A simulation layer which can forward predict control strategies to optimise the automation layer (e.g. optimum heat start up).

The management of the layers is performed by a BEMS controller, which was programmed to carry out the layer functions.

3.2.1 BEMS controller

An embedded plug computer (Sheevaplug) was chosen as the BEMS controller. It is cased in an extremely small form factor, packaged into the size of a small AC adaptor. Consuming less than 5W, and with a hardware specification including a 1.2Ghz ARM processor, 512MB RAM and no moving parts, made it a robust processing unit that required to run continuously and provide all the monitoring and control duties that is required from a typical BEMS.

The Sheevaplug has three interfaces (USB, SD, and Ethernet), with a Linux Operating System (Debian) installed on the SD card. The USB interface was expanded to connect wired and wireless sensor and actuator networks for the monitoring and control layer.

Figure 3.1 shows the complete setup used for the implementation. The Sheevaplug (1) connects to a computer network using an Ethernet connection (2), with a static IP address assignment and port forwarding of HTTP traffic so that a web based user interface can be accessed via the internet. The USB (3) connection is used for general input/output communications, and a USB hub provides connectivity to a Z-Wave wireless network used for control (6), 1-Wire sensor network for environmental monitoring and Current Cost energy monitor to measure energy consumption (9). A hard drive is also connected (5) to the hub, and is used to log data. The 1-Wire USB (7) is connected to a 1-Wire hub (8) which extends connectivity to various 1-Wire sensors, installed throughout the house.

The BEMS can monitor and control various zones in the house (Table 3.1). These zones are divided by rooms and areas. There are electric heaters in the Garage, Family Room and Master Bedroom, which have been programmed to be controlled by the BEMS.

3.3 Monitoring Layer

The monitoring layer comprised two subsystems to monitor the environment and energy consumption. The environment monitoring layer was built upon a

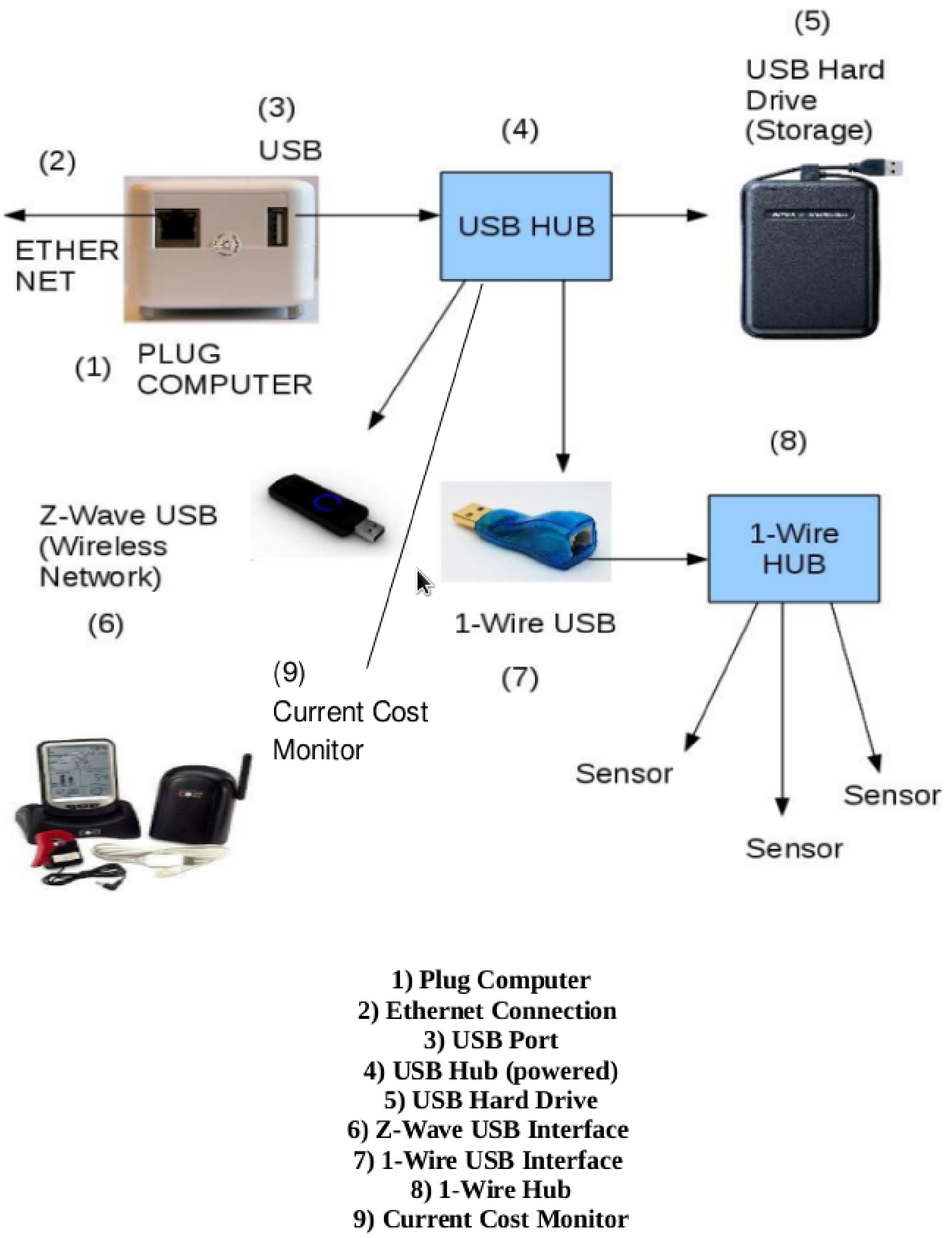

Figure 3.1: Complete System Setup

Table 3.1: Zones and Instrumentation

Zone	Sensors	Actuators
Garage	Temperature, Carbon Dioxide	Heating & Lighting
Family Room	Temperature, Luminance	Heating & Lighting
Bedroom 2	Temperature	Lighting
Bedroom 3	Temperature	Lighting
Master Room	Temperature	Heating & Lighting
Kitchen	Temperature	None

1-Wire network of sensors which monitored temperature, humidity, light levels and carbon dioxide (Table 3.2). The energy monitoring layer was composed of a wireless network of Current Cost appliance monitors. A time-series database (RRDtool[1]) was setup to periodically store the monitored data on a hard disk drive.

Table 3.2: Sensors used in the 1-Wire network

Measurement	Sensor	Unit
Temperature	Maxim DS1820	Celsius
Humidity	Honeywell HIH-4031-001	Relative Humidity
Light Level	Clairex CLD240	Lux
Carbon Dioxide	SenseAir K30	ppm

3.3.1 1-Wire Sensor Network

The 1-Wire sensor network (Table 3.2) was distributed throughout the house using Category 5 Ethernet cabling. In some parts of the house 1-Wire sensors were 'daisy-chained', whereby a sequence of sensors could be connected

[1]RRDtool -http://www.rrdtool.org/

together (Figure 3.2) and in other parts a 5-channel hub was used to extend the 1-Wire network into different rooms. Each 1-Wire sensor had a unique address, which was polled to retrieve environment data every minute and stored to the database, using the One Wire File System (OWFS)[2] software library. OWFS represents a 1-Wire network as a virtual Unix-style filesystem, whereby sensors are analogous to files. Each sensor 'file' contains the current value of the sensor, which can be read in the same way a standard file is.

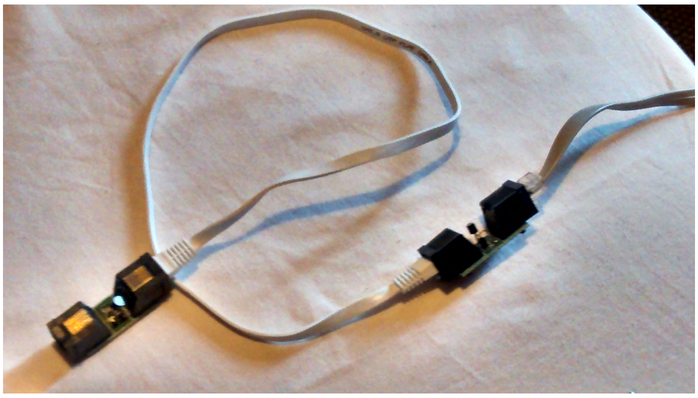

Figure 3.2: 1-Wire sensors can be chained together.

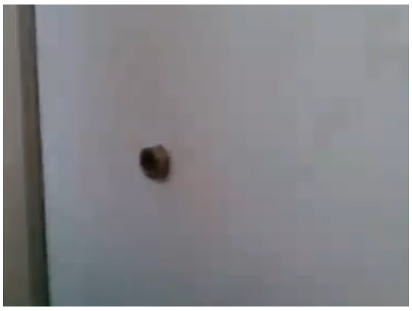

Figure 3.3: 1-Wire Temperature Sensor applied to fixture in wall

In the test house, measurements for temperature were taken for rooms specified in Table 3.1 and a humidity measurement was also taken for both the first and ground floor. Carbon dioxide was measured in the Garage and revealed occupancy patterns (Figure 3.4). Most sensors such as in Figure 3.3

[2]One-Wire File System - http://owfs.org/

were mounted at head level on the walls, in areas which were not reachable by direct sunlight.

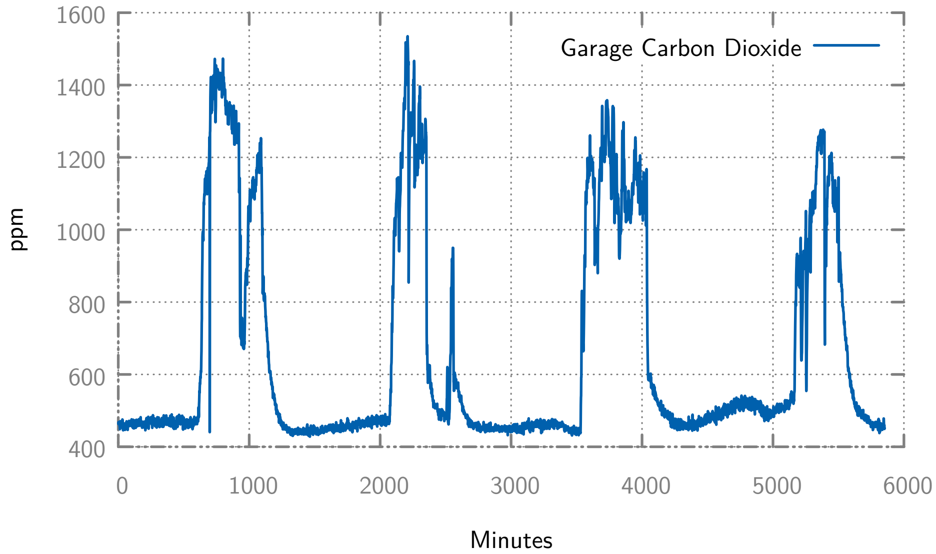

Figure 3.4: Carbon dioxide measured in Garage, revealing occupancy patterns

Figure 3.5: Weather Station was built to measure Solar Radiation and Humidity.

Light level measurement was monitored externally, along with humidity from sensors housed in a purpose built wired weather station mounted on the roof of the protruding garage (Figure 3.5). The light sensor was calibrated with a standard lux meter. Solar radiation could then be calculated using *lux*0.00402* [Thimijan and Heins (1983)]. An external temperature sensor was wired at the rear of the house, away from direct sunlight. The data was also shared with the Weather Underground for archiving purposes for the year of 2012 (Figure 3.6).

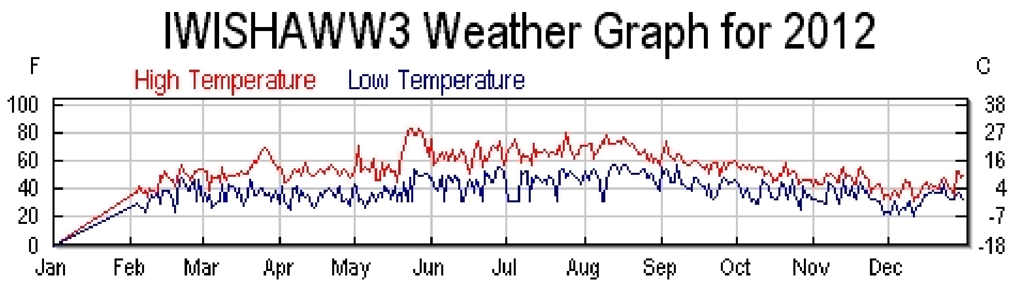

Figure 3.6: Weather Underground plot of high and low temperature captured from External Temperature Sensor

3.3.2 Energy Layer

A Current Cost energy monitoring solution was used to measure the aggregate electricity consumption at the meter, and three individual appliance monitors (IAMs) were used to measure the electricity consumption from the electric heaters to determine the heating load (Figure 3.7).

Figure 3.7: Current Cost IAMs

The Current Cost system communicates using a 433 Mhz based wireless protocol, and only measures current from a wireless current transformer (CT) clamp for aggregate measurements and from individual appliance monitors. In the UK the Current Cost monitors assume a voltage of 240V. Each IAM and CT transmitter is set up to transmit effective power readings every 6 seconds to the Current Cost base unit (Figure 3.8).

Figure 3.8: Current Cost Kit, Display, USB-Serial Cable and Clamp

The base unit also contains a simple display to show instantaneous and historical energy readings. It forwards energy data through a USB-Serial connection to the Sheevaplug, and the data is captured and stored in the database, and later processed as hourly heating loads as shown in Figure 3.9.

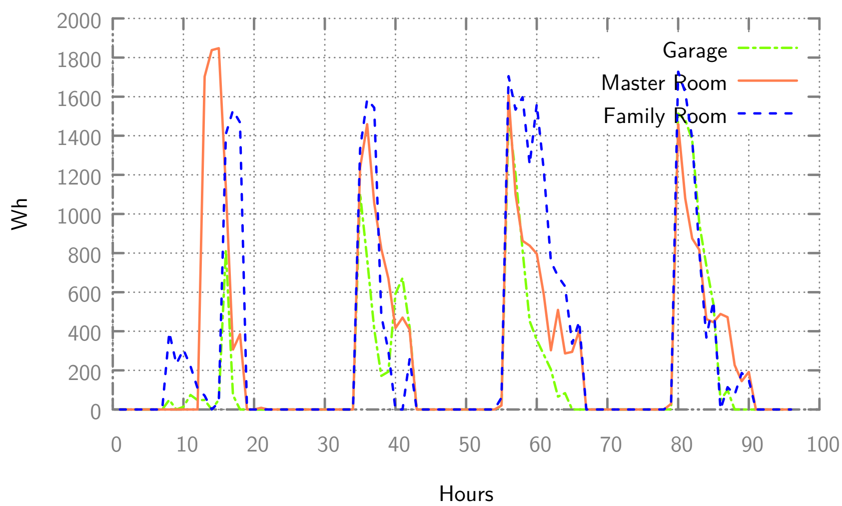

Figure 3.9: Heater Loads captured from IAMs

3.4 Control Layer

Control was implemented using Z-Wave which is a wireless protocol operating on an 868 MHz frequency. A Z-Wave network of wireless light switches and appliance modules (Figure 3.10) to control the heating was created. An Aeon Labs USB interface connected to the Sheevaplug was used to relay commands to the Z-Wave network, using a Z-Wave perl library[3].

Figure 3.10: HomePro Z-Wave ZRP210 Appliance Module

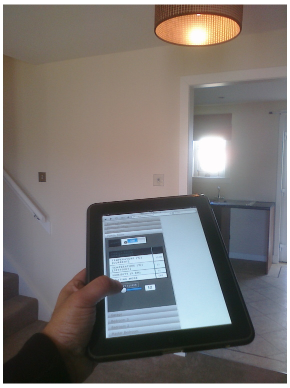

Figure 3.11: Touchscreen devices could utilise gesture control to interact with lamp brightness

A web interface was built, and lights could be controlled using on-screen buttons and gestures (swipe up to brighten, down to dim) on a touch screen interface (Figure 3.11). The interface was created using the jQuery Javascript

[3]Z-Wave with perl 'proof of-concept' - http://www.bigsister.ch/zwave/

library, and coupling it with a Z-Wave perl library, which carried out Common Gateway Interface (CGI) requests on an Apache web-server.

Figure 3.12: Setting the setpoint below current temperature deactivates heating

Figure 3.13: Heating is active

3.5 Automation Layer

The automation layer comprised automatic control systems for heating and lighting.

Setpoint control of Heating

A setpoint is a desired temperature that is 'set' in the web interface shown in Figure 3.13. A simple on/off algorithm was used to maintain temperature in rooms that had heating control. The heating system is temperature controlled using the 1-Wire temperature sensors in combination with the Z-Wave appliance modules connected to room heaters, which are turned on

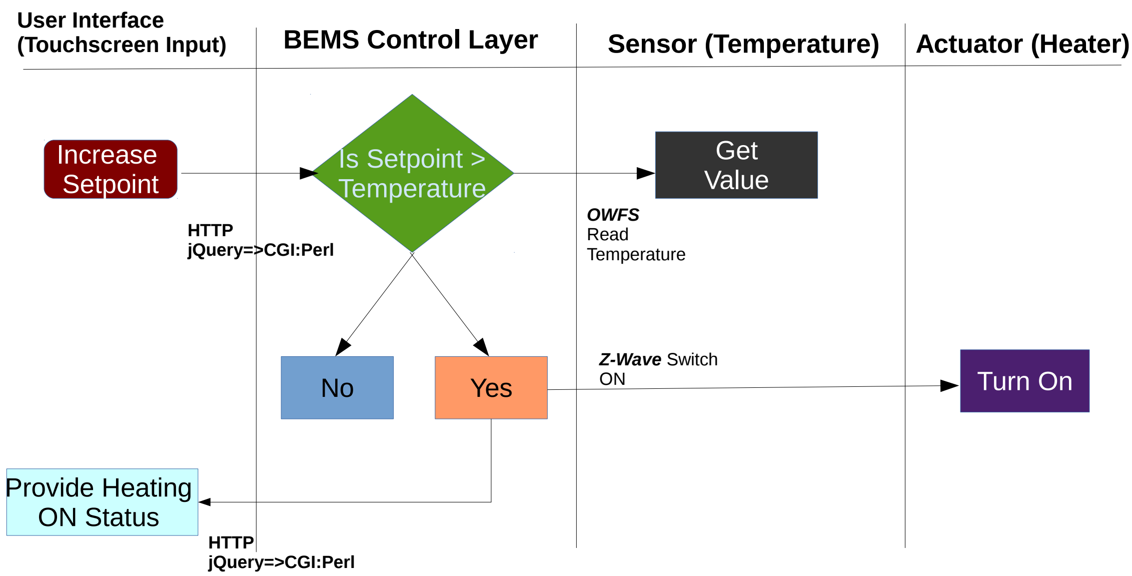

Figure 3.14: Activity Diagram showing the flow of processes for increasing setpoint from a User Interface

automatically when the temperature sensed in the room is below the setpoint (Figure 3.13), and turned off (Figure 3.12) when the setpoint is reached or is below the current temperature. The workflow process and system calls are shown diagrammatically in Figure 3.14. The touchscreen interface makes a HTTP request to call the BEMS control layer through a web server. This request is passed to a heater function in the BEMS Control perl library, which then calls the One Wire File System (OWFS) function to read the temperature file of the zone temperature sensor. Once this value is retrieved it is checked against the setpoint which has been selected. If it is above the current temperature, then the BEMS control layer calls the Z-Wave function to switch on the associated heater. Finally the BEMS control passes an HTTP request to update the user interface to show that the heating has been activated (shown as *Heating ON* in Figure 3.13). If it the setpoint is below the current temperature (as in Figure 3.12) no action is taken. By default, the heater function was active between 6am - 5pm every weekday, which represents a typical scheduled rule-based BEMS function which can be optimised as part of an efficient heating start up control strategy using the simulation layer.

Daylight reactive setting for dimming of lights

Using the light sensor mounted externally, Z-Wave lights were dimmed according to the amount of daylight, when the reactive dimmer mode was set. This mode ensures that lights are not on, when enough natural daylight can be used, or reduces the brightness accordingly, by carrying out a daylight factor calculation.

3.6 Simulation Layer

The simulation layer consists of the ESP-r BEPS software, which has been compiled to run on the Sheevaplug and can be used to generate predictive control strategies for the heating, such as optimum heat start up. The simulator requires a building model of the test house, that has been appropriately validated so that it can make useful predictions.

This thesis proposes the use of a BIM inspired simulation model, i.e. one that is built from an existing building information model, that contains not only the geometry, but additional building parameters that relate to the thermal characteristics of the building, in terms of wall constructions. BIMs also store information about the building plant, such as HVAC systems, and can also define sensor types and locations. The main benefit of using BIM for simulation in BEMS is to reuse the data already available about the building, rather than developing a model from first principles.

There was no BIM created for the test house, so the method of using a BIM was emulated by using data that would be available to create one. This data includes the geometry of the test house, based on 2D floorplans provided by Enemetric and details of sensors, control strategies and other building parameters relating to the building's insulation, that are needed for a simulation assisted BEMS to accurately perform prediction. It will be demonstrated later that having a BIM inspired model is more desirable than developing a model with less knowledge and applying calibration to try and fit parameters in Chapter 5, as part of a study into model uncertainty.

3.7 BEMS evolution and iterations

The BEMS controller evolved through several iterations during the study. The first iteration was based on LinuxMCE (Media Center Edition), an open-source project which was forked in 2008 from a previous commercial home automation solution, Pluto, first released in 2004. LinuxMCE is based on the Ubuntu distribution (Kubuntu KDE variant), and adopts much of the original Pluto concepts as an all-in-one home automation solution (supporting several protocols, notably Z-Wave), further integrating VOIP telephony, media services, (e.g. movies, music) and security. Unfortunately, it was only supported by a handful of enthusiasts, and harnessing control of the system was difficult, as the system was documented for developer use only, and proved to be quite complex, in terms of the various functions offered. It is however the basis of a closed source and expensive home automation solution from a UK company called Dianemo. The second device trialled was the

Vera Smart Home controller by Mi Casa Verde, which though added better compatibility of sensors, had bottleneck issues due to infrequent refreshing of sensors (long latency) in the monitoring layer. This was mainly due to the restrictions in the wireless Z-Wave protocol when used for monitoring temperatures. The Vera also has its roots in LinuxMCE, carrying over the Z-Wave component, which proved to be reliable for control only. Based on these experiences the author decided that Z-Wave would be a suitable solution for the control layer, and that wired sensing (rather than wireless) would offer a more robust and direct approach for data acquisition leading to the adoption of 1-Wire in the monitoring layer due to its short latency characteristics. This led the author to develop the BEMS using existing software libraries for Z-Wave and 1-Wire and combining them to create the automation layer.

Several user interfaces (Figure 3.15 - 3.18) were also designed and developed using web technologies (Apache Web Server, jQuery) to allow interaction with the system to control the lighting and heating systems, whilst demonstrating real-time monitoring capabilities. The final interface design (Figure 3.16) was entered into a BRE Smart Homes Apps competition in 2011 and reached the Final Round, where the author had the opportunity to give a live demonstration remotely of the system's capabilities at BRE Watford, and present the concept of simulation assisted control.

3.8 Summary

In this chapter, the various components of the BEMS experimental setup have been discussed, in terms of monitoring, control and automation. The key functions and methods of operation to automate and interact with heating and lighting facilities have been highlighted, with a particular focus on

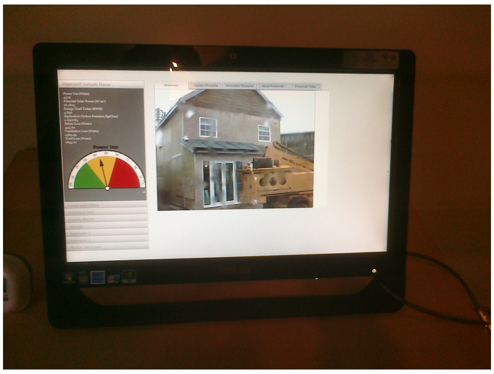

Figure 3.15: Touchscreen PC interface with Live Webcam image

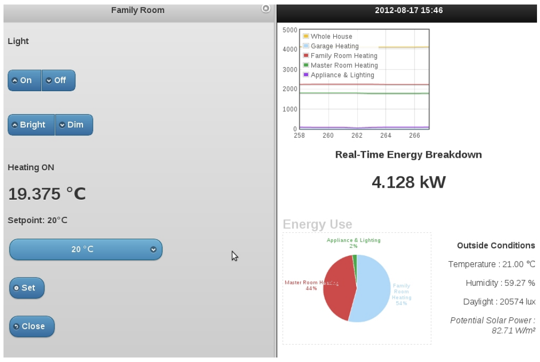

Figure 3.16: Control and Monitoring Page

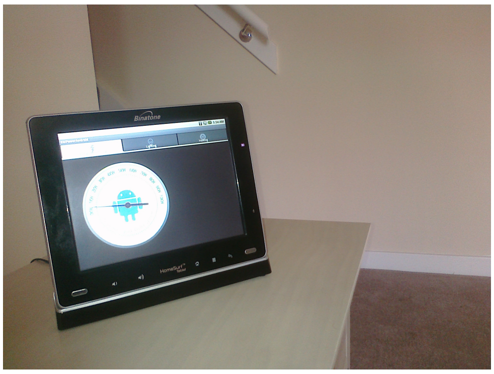

Figure 3.17: Android tablet showing Live Energy Monitoring app

Figure 3.18: Touchscreen wall monitor interface

the heating control system created as it will be replicated in the BEPS for comparisons of measured and simulated system behaviour. Finally, details of the data acquisition of BEMS energy and environmental monitoring have been elaborated on. This data will be used to aid the evaluation and validation of the BEPS model for its ability to be used in a predictive BEMS control application.

Chapter 4

Building Simulation Model Composition

4.1 Introduction

This chapter will present the building model used in the BEPS, and describe its data structure and highlight some of the details required in its composition to perform simulation. Finally, it will be shown how the BEPS model can be integrated with the BEMS to generate simulation assisted control strategies.

4.2 Enemetric Test House

The Enemetric test house used in the study is a typical family-sized home. It consisted of two floors, and was composed of a total of six prefabricated modules in a 3x2 configuration with a roof module. The house was situated on Enemetric's own off-site manufacturing facility, and was used to demonstrate

Figure 4.1: Enemetric Sample House

their construction process. Individual modules were built and finished in the factory, which is at the rear of the building and visible in Figure 4.1. The building exhibits some interesting features as it is a demonstration facility. The north, east and west façades have no external render finish, with only an exposed honeycomb layer, which is a fully vented and drainable panel made from aluminium (Figure 4.2).

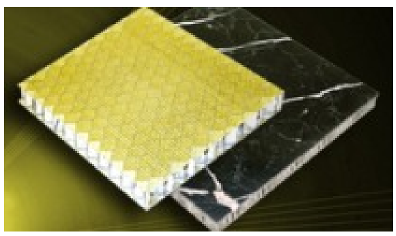

Figure 4.2: Enemetric Honeycomb Panel

Enemetric have developed this honeycomb layer to replace conventional brick layers which can be covered with a variety of finishes, such as render, brick slips marbles, ceramics, granite, stone and mosaics. The north facing façade (rear of the house) has no insulating materials. Only the south façade has external render screed applied.

The top floor had one bathroom, and three bedrooms (one master with en-suite). The bottom floor, connected by an internal stairwell shown in Figure 4.3, had a bathroom, kitchen, living room, an entrance hall and a garage which was converted for use as an office space. The front façade of the house was south facing, and could be affected by excessive solar gains as shown in Figure 4.4, especially with no immediately adjacent buildings to counter these effects with shading. This has the most effect in the garage-office space, which has two large French window doors.

Figure 4.3: Enemetric Sample House : Skeleton View showing Modular Detail

The only occupied room was the converted office garage area, which was used by two researchers (one being the author) to work and carry out research and testing.

4.2.1 Building Model

As opposed to black and grey models used in MPC, white box physical building models used in SAC are created from existing building geometry,

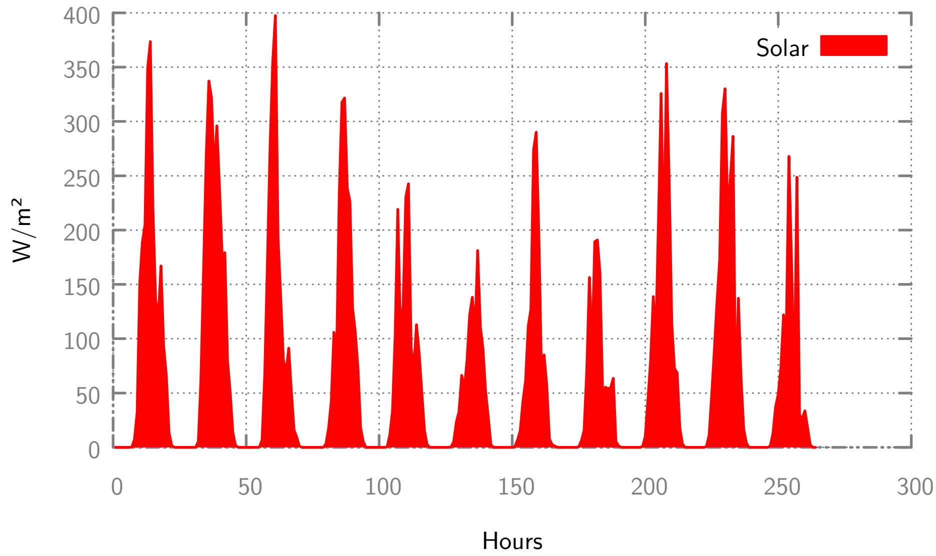

Figure 4.4: Solar Processes during April 2012

construction and operational information, and can be directly interpreted by a building simulator to carry out simulations that model physical interactions in buildings.

The building model in this thesis was created using building information supplied by Enemetric since they were not using BIM technology to maintain building data.

This information consisted of full geometric specifications, in the form of 2D floorplans, and detailed information about the construction of the walls was also provided, through enquiry.

In ESP-r the BEPS model requires a building to be divided into a number of zones. This is shown in Figure 4.5, which diagrammatically describes ESP-r's data model, where a Building is decomposed into n Zones (Figure 4.7). In ESP-r, a zone is a volume of air or thermal space, which is assumed to be well mixed and bounded by closed polygons. In ESP-r these polygons are 2D surfaces, representative of walls, ceiling or floors, which have their

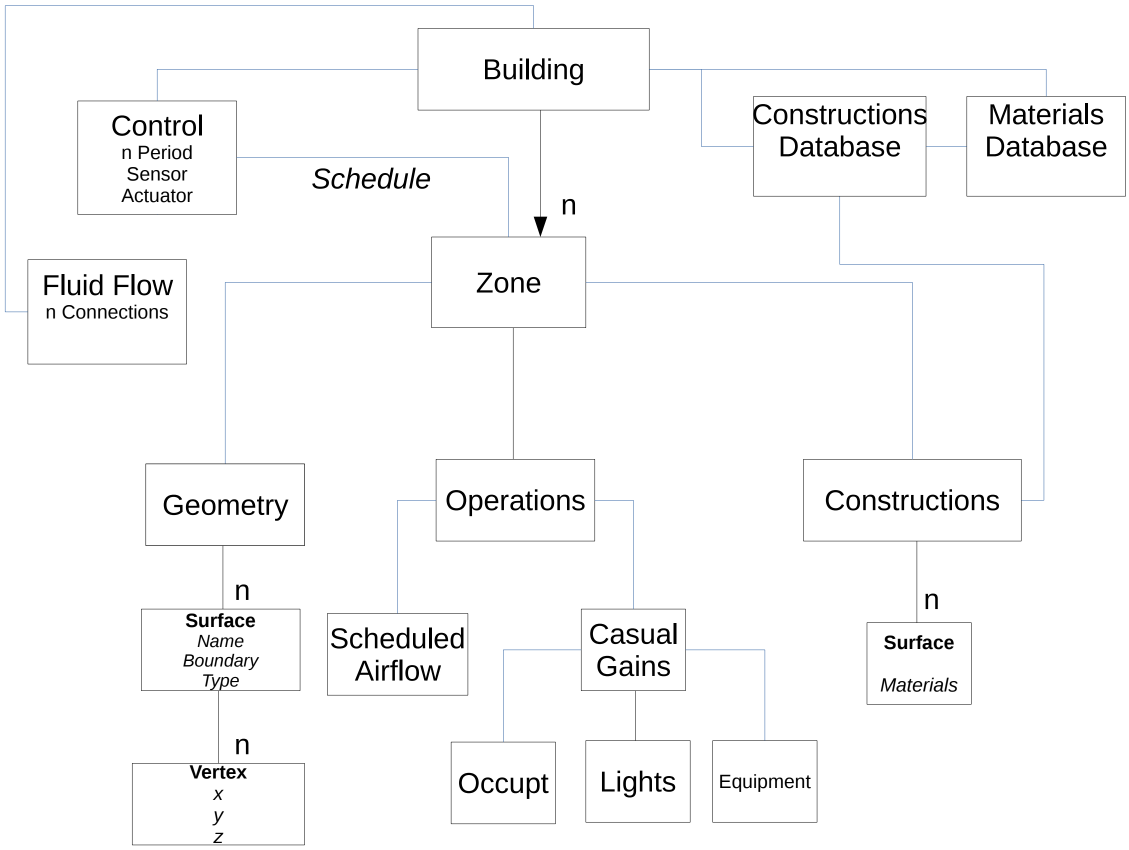

Figure 4.5: ESP-r data model.

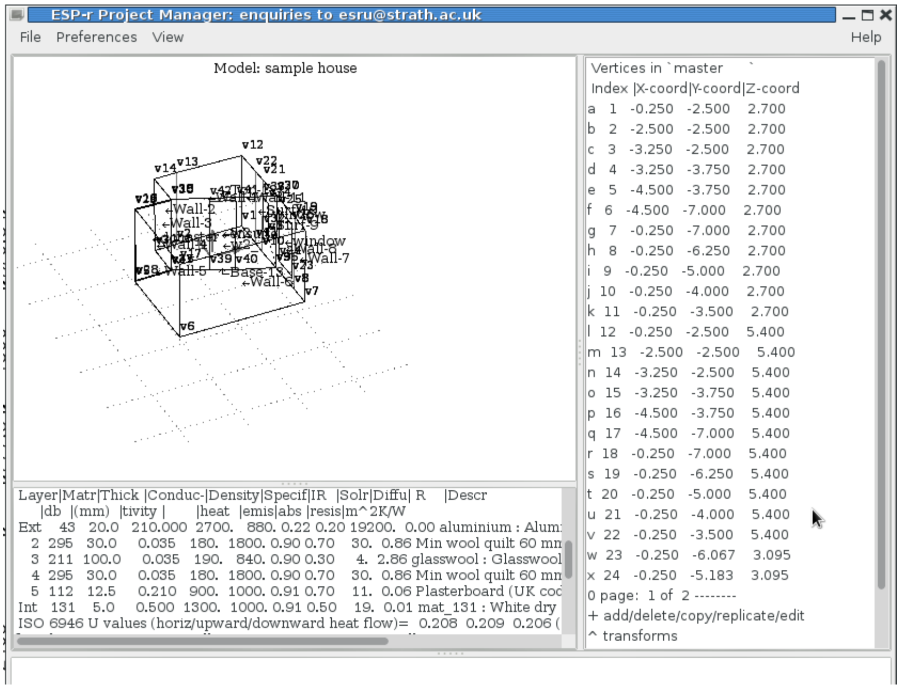

Figure 4.6: GTK Interface showing location of Vertices

corners specified in 3D space by *x,y,z* coordinates called vertices (Figure 4.6). Geometrically a zone is composed of joining these surfaces so that the space is enclosed. Additionally a window or door can be specified within a surface. This information is described in an independent geometry file for each zone, which specifies *n* surfaces. Each surface has a defined type - a construction. Each construction is composed of a number of material layers, and definitions are stored in the constructions database. A further zone construction file describes *n* surfaces and the associated materials that make up the surface. All zones will have a relationship with an adjacent zone, through a surface. This relationship is defined in the geometry file description. Surfaces essentially have two sides, one facing the zone (inside) and the other connected to a boundary condition (another zone, ground, outside). Individual walls can be entered into a zone to separate areas. In the ESP-r data model, each zone also has an operations file which describes scheduled operations such as casual gains (occupancy, lights and equipment).

A zone is the primary reporting and descriptive unit in ESP-r and is used to represent a range of spaces which are a direct mapping from reality, e.g. a room, a portion of a room or a concatenation of several rooms. During a simulation, a zone is approximated to a node in a model that represents a number of variables such as temperature and pressure, which is calculated at each specified time-step. In this thesis, temperature will be one of the variables under consideration when determining the goodness of fit, when comparing with monitored temperature data from the BEMS every hour. Other types of node include a specific load, such as casual gains or heating loads, that act on zones. Heating load will also be the focus, when determining overall goodness of fit between measured and simulated data.

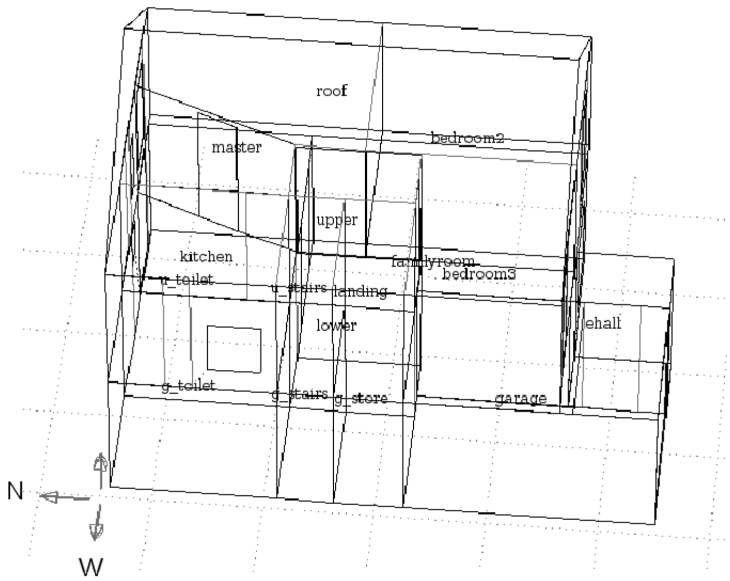

Figure 4.7: Complete house model showing individual zoned areas.

4.2.2 Surfaces (Constructions)

The following surfaces were created for the house model in the constructions databases, using ESP-r's existing materials. The list of material properties used is shown in Table 4.1. The only modifications made were to the density of mineral wool and glasswool insulation in the material's database. The mineral wool value was determined from an Enemetric brochure. The glasswool insulation density was the only unknown, but was determined to be 190kg/m^3 using calibration which will be discussed in Chapter 5.

Material	**Conductivity** (W/m·K)	**Density** (kg/m^3)	**Specific Heat** (J/(kg·K)
Dry Render Screed	0.5	1300	1000
Aluminium	210	2700	880
Mineral wool quilt	0.035	180	1800
Glasswool	0.035	190	840
Plasterboard	0.210	900	1000
Plywood	0.150	700	1420
Roofing Felt	0.190	960	837
Gypsum Board	0.160	800	1090

Table 4.1: Material Properties

Thickness (mm)	**Material**
12.5	Plasterboard
30	Mineral wool quilt
12.5	Plasterboard

Table 4.2: Internal Wall Construction

Table 4.2 shows the internal wall construction. It consists of three layers - two outer layers of plasterboard at a thickness of 12.5mm and a layer of mineral wool quilt insulation with a thickness of 30mm and a density of 180 kg/m^3. This construction was used to represent internal partitions, which are walls between rooms.

Thickness (mm)	Material
20	Aluminium
30	Mineral wool quilt
100	Glasswool
30	Mineral wool quilt
12.5	Plasterboard

Table 4.3: External Wall Construction

Table 4.3 shows the external wall construction. It consists of five layers. The outer layer is specified as aluminium, which represents Enemetric's 20mm honeycomb layer. The next three layers are composed of insulation materials, 30mm of mineral wool quilt with 180kg/m^3 density, 100mm of glasswool with 190kg/m^3 density and a further 30mm of mineral wool quilt. The final layer is composed of standard plasterboard with 12.5mm thickness. Variations of this construction are shown in Tables 4.4 and 4.5, which shows the composition for the external wall with no insulation as used in the north façade, and composition for the finished external wall as used for the south façade at the front of the house respectively. The complete external wall with render is shown in Figure 4.8.

Thickness (mm)	Material
20	Aluminium
160	Mineral wool quilt
12.5	Plasterboard

Table 4.4: External Wall Construction (No Insulation - North façade)

Table 4.6 shows the composition of the ceiling for the first floor zones. It is composed of two outer plasterboard layers, with an internal insulation layer of 190kg/m^3 density glasswool at 150mm, which is the widest thickness of insulation in the house.

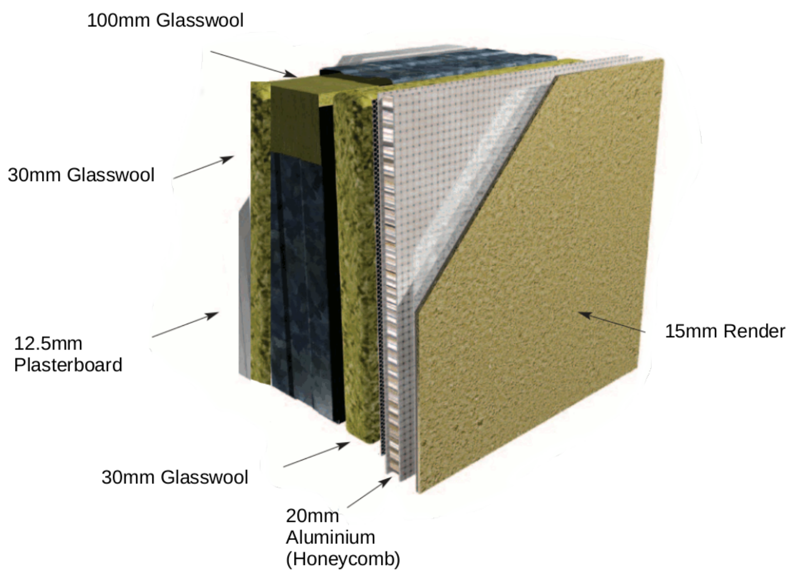

Figure 4.8: Complete External Wall

Table 4.7 shows the composition of the ceiling for the ground floor zones. It is composed of 6mm wool carpet as the top layer, for the floor of the first floor ceiling, followed by a 30mm layer of gypsum board, a 300mm air cavity, 30mm of gypsum board and 12.5mm layer of plasterboard, acting as the ceiling for the ground floor rooms.

Table 4.8 shows the composition of the front and back façades for the roof. These are finished with 15mm of dry render screed, followed by 5mm layer of roofing felt and 12mm layer of plywood. Table 4.9 shows the composition for the sides of the roof, which were not finished with an external render layer, and left exposed.

Doors were specified as oak, using ESP-r's existing definition. Windows were specified as double glazed.

Thickness (mm)	Material
15	Dry Render Screed
20	Aluminium
30	Mineral wool quilt
100	Glasswool
30	Mineral wool quilt
12.5	Plasterboard

Table 4.5: External Wall Construction (South façade)

Thickness (mm)	Material
12.5	Plasterboard
150	Glasswool
12.5	Plasterboard

Table 4.6: Ceiling First Floor

4.3 Zoning Strategy

In order to have a fully coupled simulator with building energy management system, the simulation model is divided into zones corresponding to the controllable zones in the BEMS.

This differentiates from typically used core and four perimeter zones method [Raftery *et al.* (2009)], where zones could be a concatenation of several rooms, and in fact will provide a model that is more akin to reality, and actual building operation.

A requirement for predictive simulation assisted control, where individual rooms could be queried for a control prediction, would be to zone each room and treat it as bounded thermal space.

Thickness (mm)	Material
6	Wilton weave wool carpet
30	Gypsum board
300	Air
30	Gypsum board
12.5	Plasterboard

Table 4.7: Ceiling Ground Floor

Thickness (mm)	Material
15	Dry Render Screed
5	Roofing Felt
12	Plywood

Table 4.8: Roof Front and Back

Taking this into account, the building model has been divided into 16 zones, and the zones have been developed from actual room dimensions, based on the original floor-plans. The X11[1] interface has been used which allows importing of 2D plans as a bitmap, which can then be 'traced' to mark out the geometry into zones (essentially generating the lengths and widths of the rooms, and the height is then extruded with user defined input).

Though the model in this thesis has not been created from an existing BIM, it is worth discussing some of the issues that could be encountered, since processing of BIM geometry for building simulation is becoming an notable area of interest, with the development of the Geometry Simplification Tool by LBNL [O'Donnell (2014)], which is still not a fully automated process.

Most importantly, the main difference when translating a geometric

[1]Windowing interface system for bitmap displays, common on Unix-like computer operating systems (such as Linux). ESP-r alternatively has an option for a *GTK* interface, which is a newer interface system, but lacks the tracing function.

Thickness (mm)	Material
5	Roofing Felt
12	Plywood

Table 4.9: Roof Sides

architectural model to a simulation model with thermal characteristics, is the treatment of walls. Figure 4.9 shows two different perspectives and considers the separation of three spaces using a wall with an opening between the smallest two spaces. It can be seen from the architectural geometric perspective that there are essentially three walls. The largest wall separates the largest Space 3 with the smaller Space 1 and 2. The two smaller walls separate Space 1 and 2, with an opening space between them. From this architectural point of view, Space 1 and 2, could be considered as one large room, since there is an opening between them. Building simulators however require spaces to be explicitly defined and fully bounded as zones in order to carry out thermal simulation. This poses an interesting problem. Since there is no door, an imaginary wall is required to be specified. ESP-r has a construction to deal with issues like this called *"fictitious"* construction layers. These layers are walls which are very conductive, have no appreciable thermal mass, are perfectly transparent and have no solar absorption. In Figure 4.9 this has been represented as Boundary 4 in the thermal simulation perspective, with the other walls dividing Space 1 and 2, represented as individual Boundaries 3 and 5. Similarly the wall separating the larger Space 3 with the other two spaces needs to be divided, so that it has individual thermal relationships with each of the smaller spaces. In this case, it has been divided into Boundary 1 and 2. With these boundaries in place, the spaces are now fully zoned.

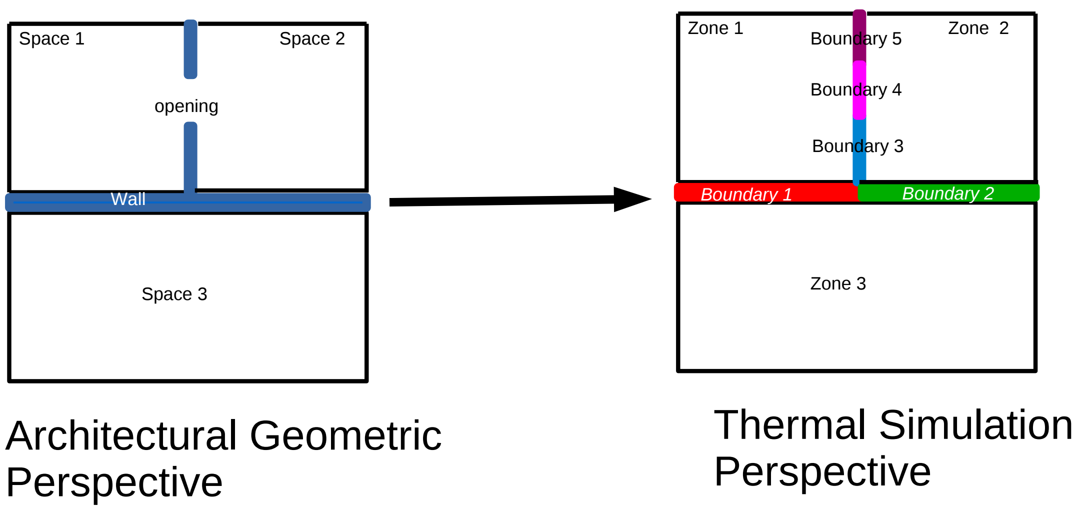

Figure 4.9: Architectural Walls and Thermal Zone Boundaries

4.4 Ground Floor Zones

The ground floor as show in Figure 4.10 has been zoned into the following. Each floor facing surface has been specified using ESP-r's default construction.

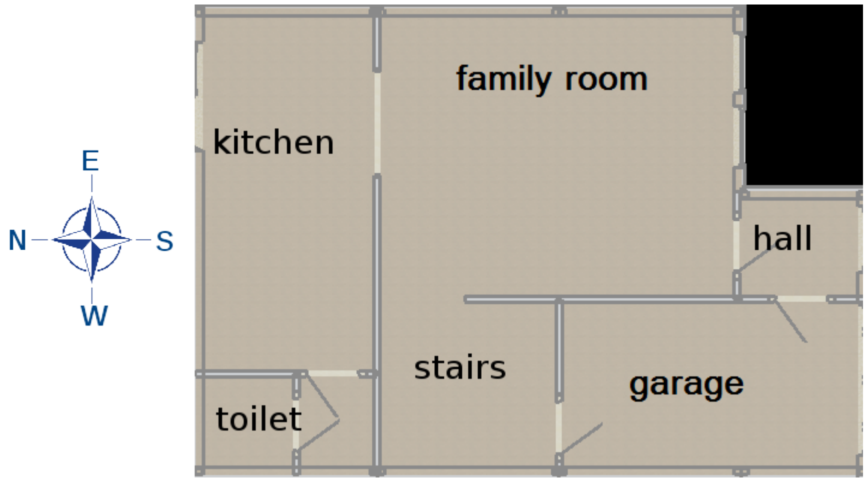

Figure 4.10: Ground Floor Plan

1. **Hall** - this is the main entrance to the house, which shares internal wall construction surfaces with the Family Room and Garage, and has two external facing surfaces. There is an external door, specified in the south facing external surface. In ESP-r this door is specified as closed. There are a further two internal doors to the Family Room and Garage, also specified as doors as shown in Figure 4.11. These doors have 'cracks' for airflow which will be discussed later.

2. **Garage** - this was originally specified as a garage, but converted into an office, with two desks. The name of the zone *'Garage'* has however remained to describe this space. It shares an internal wall construction with the adjacent Family Room, Hall, and Stairwell zones. The west facing wall is specified as external wall construction surface. The main feature of the Garage is the large south facing double glazed French

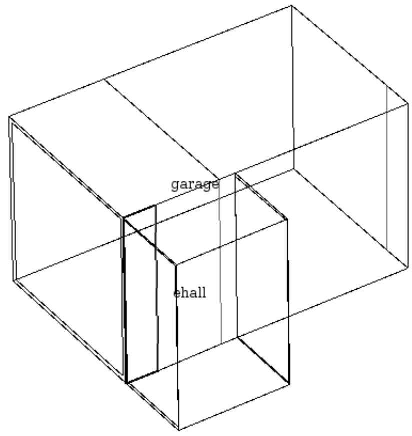

Figure 4.11: The Hall has three doors, to the Garage, Family Room and External Environment. The Garage has a large window opening representing double glazed French doors.

doors, which has been specified as a large window opening as can be seen in Figure 4.11, ignoring the panes, as seen in Figure 4.1.

3. **Family Room** - this is an open living area, with no furniture. It shares its internal construction boundaries with the Kitchen, Garage and has a door to the Hall, which is specified as closed. The east wall is an external facing construction, and the south facing wall has a window construction. In Figure 4.12, it can be seen that the Kitchen connects to the Family Room via an opening with no door. Here an example of the use of *"fictitious"* construction being used to represent this opening. An alternative method would be to model the Family Room and Kitchen as one zone and insert wall partitions to separate the zones, but then the individual room characteristics would be lost, and room level predictions would not be possible. Similarly, as shown in Figure 4.12, the fictitious layer is used for the stairwell boundary.

4. **Kitchen** - this is a fully fitted modern Kitchen area, albeit without any facilities such as water or gas for cooking. The north facing wall has a

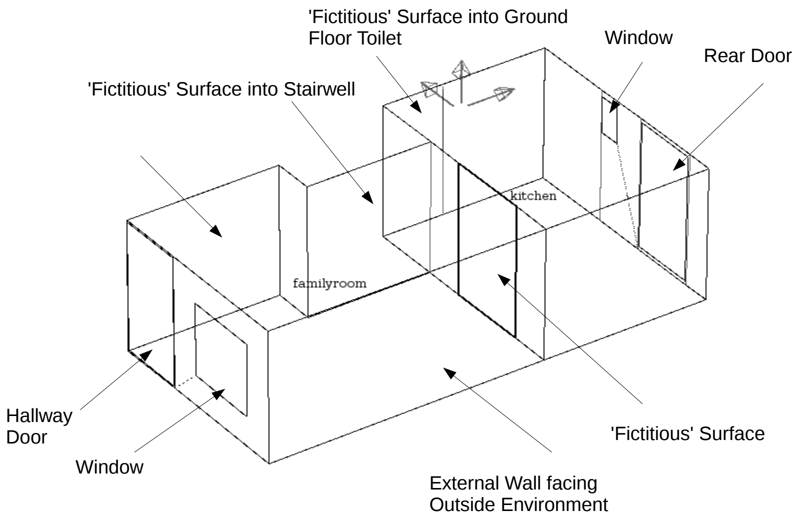

Figure 4.12: Kitchen - Family Room relationship

small window inserted into the surface and a glass rear door, which has been modelled as a large window. This wall also has no insulation using the construction specified in Table 4.4. The Kitchen's west facing surface is shared with the ground floor toilet at the rear of the house as shown in Figure 4.12.

5. **Ground Floor Toilet** is adjacent to the Kitchen, and was not operational, though did contain a toilet. There is is a fictitious construction as a boundary to the Kitchen, which can also be seen in Figure 4.12. There is a small window opening placed at the north facing surface, which has no insulation.

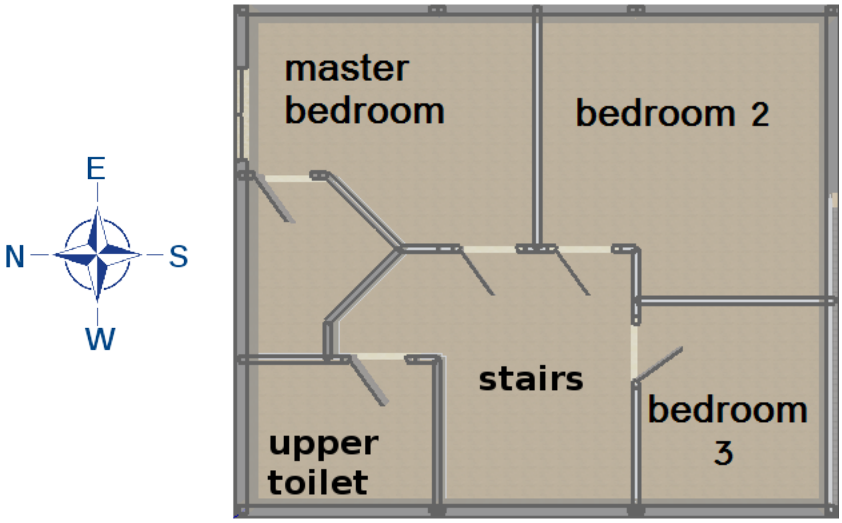

Figure 4.13: First Floor Plan

4.5 First Floor Zones

The first floor as show in Figure 4.13 has been zoned into the following. This floor mainly consists of bedrooms, with an additional toilet.

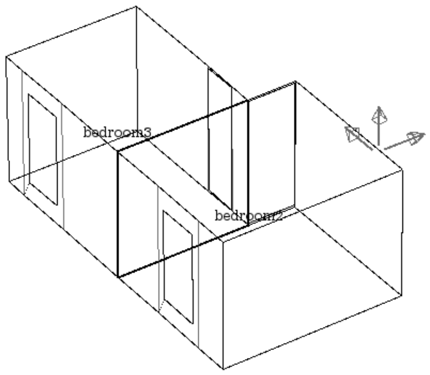

Figure 4.14: Bedroom 2 and 3 Zones

1. **Bedroom 2** is the smaller of the two bedrooms as shown in Figure 4.14, and adjacent to Bedroom 3. It has a south facing window inserted into an

external construction boundary, and a door to a landing area zone, which is specified as closed in the zone description.

2. **Bedroom 3** is similarly south facing with a window, and shares a boundary with the Master Bedroom at the north facing surface internal wall construction (Figure 4.15). There is a door construction to the landing area zone, which is specified as closed. The south and east facing walls are external construction boundaries.

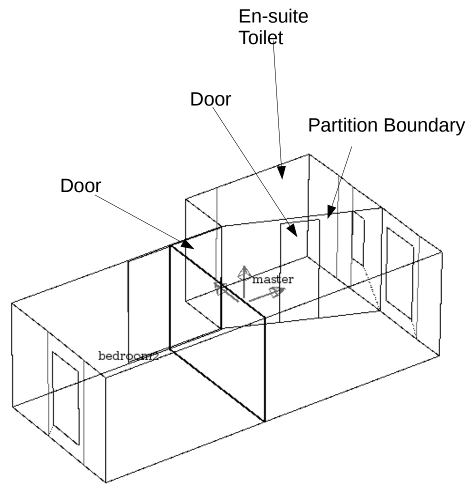

Figure 4.15: Master with En-suite Toilet

3. **Master Bedroom** is adjacent to Bedroom 3, and is at the rear of the house. The north facing wall has no insulation, and has a window inserted into the surface. This bedroom has an en-suite toilet and a bed. Technically, this toilet is part of this bedroom, so instead of modelling this area as a separate zone, a internal partition boundary has been used to divide the volume, as shown in Figure 4.15. There is an entrance door to the landing area zone, and a door to the en-suite toilet. Both doors are specified as closed in the model.

4. **First Floor Toilet** is adjacent to the en-suite toilet of the Master Bedroom. This zone has a small window inserted into the west façade surface. Similarly to the Ground Floor, it has a non-operational toilet. There is also a door to the landing area zone, again specified as closed.

4.6 Roof

The Roof is the topmost zone of the house, with the bottom layer surface encompassing all the individual ceilings of the first floor zones, as shown in Figure 4.16. All other surfaces are external facing boundaries, with definitions for both the front/back and sides, as shown in Tables 4.8 and 4.9.

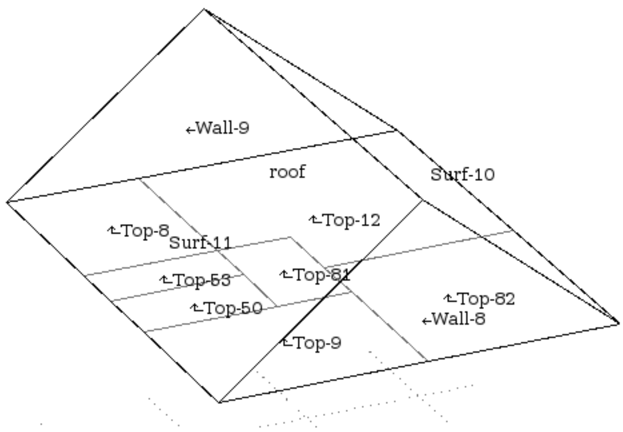

Figure 4.16: Roof Zone

4.7 Modelling of Stairwell

The stairwell is an interesting feature to model, as it is a void that connects the two floors. The steps have not been modelled, and it has been approximated as four zones, with two on the ground floor, and two on the first floor. One set of ground floor and first floor stairwell zones has been modelled with a horizontal fictitious boundary as the equivalent of a ceiling used in other zones. Vertical facing fictitious surfaces have been created on the first and ground floor zones, between the stairwell zones and the landing on the first floor and the ground floor Family Room.

4.8 Zone Controls

Heating control has been applied to the Garage, Family Room and Master Bedroom, which had BEMS controlled heaters and were automated by the system to turn on at 6am and turn off at 5pm on weekdays, representing a typical unoptimised heating schedule. The Garage and Family Room were serviced by 2000W rated oil filled radiators, and the Master Bedroom utilised a 550W wall mounted infrared mirror heater.

In ESP-r, the simplest control mechanism for heating has been applied, with a basic on/off algorithm, which actuates a heating load by sensing a zone's temperature. A building control file has been set up and associated with the model, and specifies the setpoint for zones, which is a desired temperature, the heating system needs to maintain during the scheduled hours. If the zone temperature is below this setpoint, the heating is turned on, and when it is reached, it is turned off. This method of control in ESP-r was chosen as it closely represents the BEMS mechanism of control that was implemented. It will be shown later, that the predictive capability of ESP-r can be used to optimise this heating schedule, by delaying the switch on time, so that a setpoint is reached when the house becomes occupied.

The zone's air temperature sensor is coupled with an actuator that injects heat from a specified surface in each room to maintain a setpoint. In the actual house, heaters were located on the eastward wall of each of the rooms - and similarly in the model they are located in this position.

4.9 Casual Gains

ESP-r allows user-defined hourly diversity profiles of various casual gain input, e.g. occupancy, lighting and equipment loads.

In this model, only equipment and occupancy loads are only applied to the Garage, which was used as a daily office space. For occupancy ESP-r recommends using values specified from the CIBSE Concise Handbook (A6 Internal heat gains), Table 6.1 [CIBSE (2008)]. This particular table outlines various levels of heat produced (in Watts) according to the type of work being carried out and the zone temperature. As there were two researchers working, this was accordingly specified as 140W (Seated Office Work, 20C). 100W was specified for equipment gains from two laptops and monitors. Light was not considered, as there was often sufficiently enough daylight in the space to work.

4.10 Fluid Flow Network (Airflow)

Airflow within buildings is affected by a number of processes, including unidirectional air leakage from the outside to inside, air circulating between zones, and also by air circulation within each zone. The amount of air leakage within the building envelope is influenced by external air boundary conditions (i.e. wind speed, pressure, and air temperature), and by the internal zone air temperature and pressure.

There are two main approaches to implement airflow within an ESP-r model. The first approach involves scheduling of airflow, similarly to casual gains, which disregards external boundary condition influence. In this case, the number of air changes per hour (ACH) of infiltration can be specified for a zone. 1 ACH is the equivalent of one whole volume of air being discharged in an hour. This can also be forced through a control mechanism. For instance if the temperature in a zone reaches a threshold, the infiltration rate can be increased.

However this method is imposed and does not take into account boundary conditions such as wind. A better method is to use ESP-r's fluid flow network facility. Instead of scheduling airflows, a fluid flow network represents flow paths through the building. The fluid flow network for airflow is defined by creating flow nodes, flow components and flow connections, and specifying relationships between them, as shown in Figure 4.17.

4.10.1 ESP-r Fluid Flow Network Definitions

The implementation of the fluid flow network in this model will be discussed by introducing the various parts that are used to represent building airflow.

4.10.1.1 Flow Node

A flow node is a measuring point in an airflow network for pressure, temperature, and rate of flow. The two main types are an internal node and boundary node. An internal node has been specified for each zone, and is located at the centre of a zone's air volume. Boundary nodes are wind induced, and located externally at each façade of the house. This particular type of node

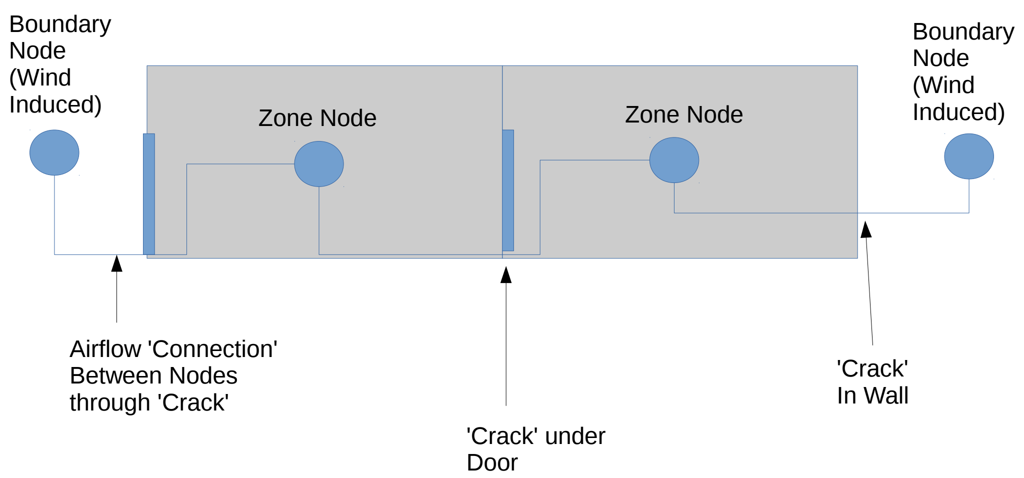

Figure 4.17: Airflow Network

represents wind pressure and is a function of wind velocity, direction, terrain, building height, and surface orientation.

4.10.1.2 Flow Component

A flow component describes the flow between nodes. Common flow components in ESP-r include fans pumps, valves, ducts, openings and cracks. The most used flow component in this model is the crack component which has been specified for all doors in the house, to connect flow nodes between room zones as shown in Figure. The width and length of this crack has been specified with a width of 10mm and length of 0.8m. The bi-directional flow component in ESP-r is used to connect zones with fictitious surfaces.

4.10.1.3 Flow Connection

Connections are defined as links between nodes using components. Zone nodes have been linked with an airflow relationship through cracks under doors, and boundary external wind induced nodes are connected to zone nodes through cracks specified in external walls. The entrance door of the Hall however has been linked to the south boundary node using a door crack component.

4.11 Proposed System Integration

Now that the components of the BEMS and BEPS model have been presented, the integration of the system to perform predictive control can be discussed.

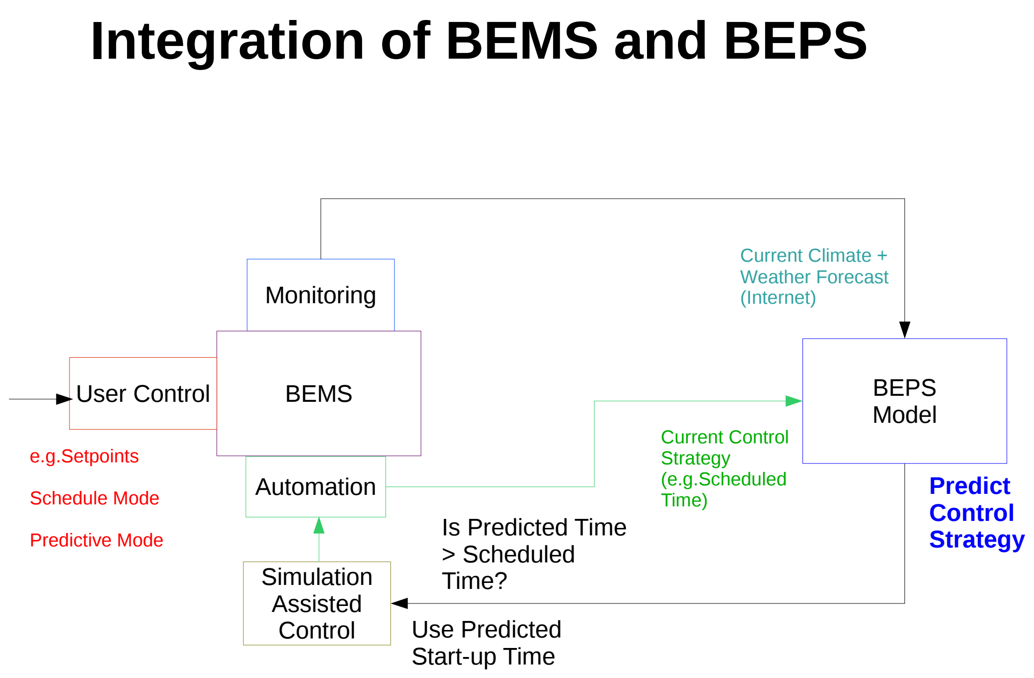

Figure 4.18: System Integration

Figure 4.18 shows how the various elements of the proposed system interact. The BEMS has several subsystems for monitoring, automation and (user) control, which were elaborated on in the previous chapter. The BEPS subsystem represents the simulation layer that enables predictive capabilities, using the building model that has thus far been presented.

An example of a predictive control strategy is to determine the optimum switch on for the heating system to reach setpoint at a particular time in the morning of the next day, when there is sufficient forecast data to do so and the predictive mode has been selected. This type of prediction is useful when there is a lookahead of several hours [Clarke *et al.* (2002)].

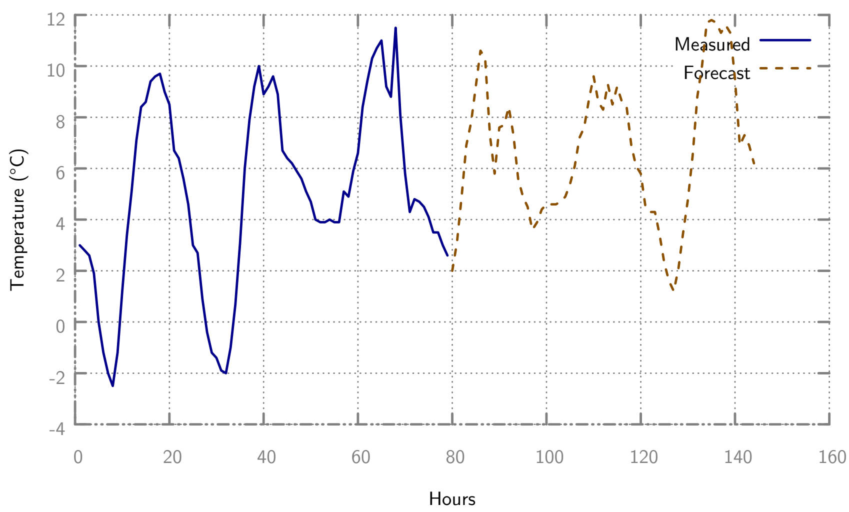

Figure 4.19: Weather Forecast

The monitoring component of the BEMS provides current climate combined with an hourly weather forecast which can be downloaded from the internet. An example of this is shown in Figure 4.19, where the forecast data is combined with the currently measured and monitored climate data for temperature. In ESP-r this is an *imposed data set*. In this example, our focus is on the forecast period after 80 hours.

The automation component of the BEMS provides the current control strategy, which in this case is a scheduled time to activate the heating, and inputs this to the control file of the BEPS model. This scheduled time could be 6am with a setpoint of 21°C to activate the heating. However the predictive mode selected has requested the setpoint to be reached at 9am (i.e.arrival time), and not before.

Since a lookahead of several hours is required, the BEMS will instantiate a set of simulation runs at 6am using the forecasted climate data to determine if the scheduled time will lead to the setpoint being reached before 9am. If the 6am scheduled time results in the setpoint being reached before 9am, the BEMS predictive mode will instantiate a set of simulations, by systematically adapting the model's control file.

There are several ways to approach this. The simplest algorithm would be to linearly carry out simulation runs and increment the start up times (say in 6 minute intervals), of the BEMS schedule control file until the simulated scheduled time (i.e. optimum heat start up time) is such that the heating system reaches the desired setpoint at the arrival time. (This method is evaluated and further discussed in Chapter 6).

Alternatively, the algorithm could consider the differences between the predicted heat time to reach setpoint and optimum heat time. In this example, if it took 1.25 hours to reach setpoint, this time could be subtracted from the arrival time of 9am to obtain an estimated start time at 7.45am. The process could then be iteratively repeated until the predicted time of reaching the setpoint is within the desired error of the algorithm.

Once the prediction is complete, the BEMS control configuration is appropriately modified to carry out the optimised schedule.

4.12 Summary

This chapter has covered the creation of a building model representing the Enemetric test house to be used in the BEPS tool ESP-r, and evaluated against the BEMS data collected for predictive simulation assisted control. Since a BIM was not available, a model has been designed as an equivalent that would contain the same level of data. The underlying ESP-r model has been discussed, including the data structures that describe the components that are need to perform building simulation, such as zones, operations, geometry, airflow and constructions. Notably individual constructions have been created which represent different façades of the house. Key zones representing the monitored rooms in the house have been explored and discussed in terms of their constructions and relationships. Following these descriptions, the integration of BEMS and BEPS has been elaborated on and the methods to carry out simulation assisted control have been explained.

The next chapter will delve into the effects of not having an ideal model presented in this chapter, by introducing various levels of uncertainty.

Chapter 5

Building Model Uncertainty

5.1 Introduction

In this chapter, uncertainty will be introduced into the building model and an attempt at calibration will be made using measured data. This will represent an analogy to a grey box model, which assumes some level of building knowledge. The effects of uncertainty will be analysed, by making assumptions on the building model due to a lack of information. It will be shown that uncertainty in a building model needs to be minimised by having as much information as possible, and that building model calibration as a method of addressing uncertainty is no substitute for a well defined model.

5.1.1 Reasons for Uncertainty

There could be number of reasons for uncertainty in a model.

1. A basic translation from a BIM. Geometry translation from BIM to BEPS models can lead to a loss of information.

2. Lack of source data about the building construction.

In either case, calibration is required to adjust the model accordingly, by comparing the output of the model with measured data. Calibration techniques and approaches will also be covered and discussed.

5.2 Introducing Uncertainty

There can be several sources of uncertainty in a model. The following sections will describe the types of uncertainty introduced in the model according to those identified by de Wit and Augenbroe (2002) in an *"Analysis of uncertainty in building design evaluations and its implications"*. Essentially an uncertain model lacks knowledge and information due to a number of unknown factors.

5.2.1 Specification Uncertainty

This relates to a lack of information on the exact properties of the building, such as the building geometry.

In the uncertain model the roof has been removed (Figure 5.1), approximating the geometry of the model. This represents a case where the geometry has been simplified, either due to a lack of information or a poor translation from a BIM.

Furthermore, the Master Bedroom does not have a partition boundary to separate the en-suite bathroom. Fictitious surfaces have still been used to

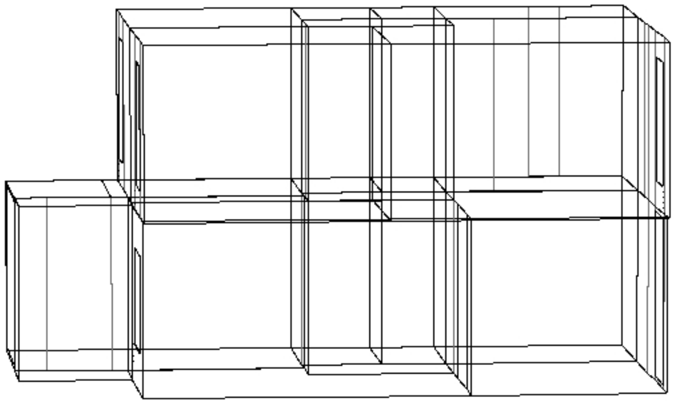

Figure 5.1: Geometric approximation - no roof, and the Master Bedroom does not have the divided en-suite section

divide open areas, apart from the boundary between the Kitchen and Ground Floor Toilet.

5.2.2 Parameter Uncertainty

There can be degree of a uncertainty for each input parameter, for example, material properties.

The uncertain model makes an assumption that the model was built with only two wall constructions:-

1. An internal wall construction representing all internal partitions (including internal ceilings and floors). This is shown in Table 5.1.
2. An external wall partition which assumes all boundaries of the house are external facing (with no roof - essentially approximating the whole top floor ceiling as an external wall construction, the same used for the walls). This is shown in Table 5.2.

Thickness (mm)	Material
12.5	Plasterboard
Uncertain Parameter	Glasswool : Insulation (180kg/m^3 density)
12.5	Plasterboard

Table 5.1: Internal Wall Construction (Uncertain Model)

Thickness (mm)	Material
20	Aluminium
30	Mineral wool quilt : Insulation (180kg/m^3 density)
Uncertain Parameter	Glasswool (10kg/m^3 density)
30	Mineral wool quilt : Insulation (180kg/m^3 density)
12.5	Plasterboard

Table 5.2: External Wall Construction (Uncertain Model)

Furthermore, glasswool is assumed to be an insulation component in both the internal and external wall constructions (rather than mineral wool) and the thickness has been chosen to be an uncertain parameter, requiring calibration.

5.2.3 Modelling Uncertainty

This arises from simplifications and assumptions that have been introduced in the development of the model.

There is no fluid flow model for air applied, though scheduled airflow is explored, further simplifying the building dynamics and physical processes.

5.3 Evaluating Uncertainty (Model Validity)

To evaluate uncertainty in a model, goodness of fit between measured and simulated model data needs to evaluated. A number of metrics can be used for this purpose. In the early years of building simulation, simple per cent difference calculations were the primary means of comparing measured and simulated data [Coakley *et al.* (2014)]. Nowadays, the majority of literature for building simulation research make use of the CV (RMSE) (Coefficient of Variation of the Root Mean Squared Error) (Equation 5.1 and 5.2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (m_i - s_i)^2}{n}} \tag{5.1}$$

$$CV(RMSE) = \frac{RMSE}{\bar{m}}.100 \tag{5.2}$$

It measures the differences between simulated (s) and measured (m) values, at each timestep i, for a total number of timesteps, n. A lower value indicates less variance and hence higher quality model. CV(RMSE) aggregates time specific errors into a single dimensionless number. It is the most used metric in building simulation model research, to validate uncertainty, and when used during model calibration, is the value sought to be minimised.

5.4 Model Calibration

To reduce uncertainty, calibration techniques need to be applied. Calibration involves modifying model input parameters, in a systematic way, until the model has passed a threshold to be deemed *"calibrated"*, according to criteria set out by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) in ASHRAE Guideline 14[ASHRAE (2002)] which uses CV(RMSE) to assist calibration, specified under section 5.2.11.3 (Modelling Uncertainty). The ASHRAE guidelines are often used to benchmark building models in the majority of calibration and validation studies for building simulation.

According to the criteria, a CV(RMSE) of 15% is acceptable for calibration models using monthly data and 30% for hourly models. Hourly data gives the most accurate results, though is the most difficult to capture; monthly data can also be acceptable depending on the application, but can mask inaccuracies that can appear at hourly or daily resolutions [Raftery *et al.* (2011)].

In a review of methods to match building energy simulation models to measured data by Coakley *et al.* (2014), it was further recognised that numerous models of the same building that could be considered to be calibrated, and that current calibration criteria relate solely to predicted energy consumption, and do not account for uncertainty or inaccuracies of input parameters, or the accuracy of the simulated environment (e.g. temperature profiles). Temperature profiles are often omitted in many calibration studies, however will be explored in this thesis. Furthermore this statement highlights the fact that calibration can yield multiple models if purely relying on statistical methods. This may provide a model that is limited in simulation scope.

In a previous review, Coakley *et al.* (2011) described three methods of calibration, contrasting the preferred evidence-based method with graphical model calibration and the statistical optimisation approach. Reddy (2006) also included manual iterative calibration, based on trial and error and tests based on analytical procedures. One cannot rely on one particular approach, and in fact will have to employ a mix of approaches. This is most apparent when calibrating or validating models using the ASHRAE guidelines which were originally specified for monthly comparisons between measured and simulated data. For example, statistically the CV(RMSE) may punish large errors during an hourly comparison of heating energy (due to comparing measured and simulated data point by point), but when viewed graphically the load profile may present a better fit and view of the data, especially when looking at the daily response. This is due to the high variability of energy delivery and complexity of interactions that BEPS tools will simply not be able to account for in their calculation engines.

Ruiz Flores and Lemort (2014) carried out a study - *"Calibration of Building Simulation Models: Assessment of Current Acceptance Criteria"* and concluded that *"[The] Current criteria are necessary but not sufficient"*. They evaluated a simple and complex model, noting that they both appeared calibrated according to the guidelines, even though the simulated response appeared graphically very different for monthly electricity consumption assessed for a year.

Issues in Coakley *et al.* (2014) with calibrated simulation were broken down into several areas, in terms of standards, uncertainty, simplification and automation. For standards it was recognised that guidelines such as those developed by ASHRAE actually specify broad ranges of allowable error for building energy models and that they do not account for issues such as input uncertainty/inaccuracy or the model fit to zone-level environmental data. In addition, it was concluded that there are no standard guidelines for model development, which leads to fragmentation of the practice of energy modelling. Indeed since there are no guidelines to model development, this leads to assumptions and uncertainty, particularly if the whole building is not modelled and zoned effectively. As for parameter uncertainty, it was alluded to as one of the primary sources and is often disregarded in BEPS calibration case studies, leading to questions over the accuracy of the model outputs. For example do the parameters fit within a realistic range? Another important issue is that of simplification, particularly when validating or calibrating to a single measurement for whole building heat energy and electrical loads. This thesis intends to explore heating energy calibration and validation at the zone level, which has never been carried out previously, as most studies deal with gas-powered (boiler) water-based heating systems, making it difficult to determine an individual zone's energy delivery.

In terms of automation, it was recognised from the survey that automation greatly aids the calibration process. Troncoso (1997), claimed many used fine-tuning methods (fudging), rather than rigorous calibration methods, which if employed were not documented, if a manual approach was taken. One of the most notable automated optimisation tools for BEPS is GenOpt developed at LBNL [Wetter (2001)]. GenOpt is a generic optimization program. It minimises an objective function with respect to multiple parameters, such as annual energy use or peak electrical demand. GenOpt has been used frequently with common building simulation programs such as TRNSYS, EnergyPlus and IDA-ICE. One of the few implementations of GenOpt with ESP-r was carried out by Peeters *et al.* (2010) to optimise window sizes. However GenOpt can also be used for calibration. Recent studies by Tahmasebi in the area of automated building model calibration using GenOpt with EnergyPlus have taken consideration of temperature profiles during calibration for office buildings [Tahmasebi and Mahdavi (2012), Tahmasebi *et al.* (2012), Tahmasebi and Mahdavi (2013)].

In these studies the CV(RMSE) is combined with another metric, R^2 (a statistical measure of how close the data are to the fitted regression line) to aid automated calibration using hourly temperature data collected by a BEMS. In Tahmasebi and Mahdavi (2012), the heating system was not considered, and the zone temperatures were averaged. Furthermore, only a single floor of the building was modelled, therefore, the floor and ceiling surfaces were assumed to be adiabatic. The variables to be calibrated included values pertaining to the external brick layer (density, conductivity, specific heat) and external windows (open, closed, glazing solar transmittance). The resulting CV(RMSE) was 3.26% for the calibration period and 2.35% for the validation period, both relatively low. A later study [Tahmasebi *et al.* (2012)], monitored radiator temperatures to derive the heating energy as simulation input, but still only considered averaged zone temperatures for temperature leading to a CV(RMSE) of 2.78% during calibration using the previous set of parameters for brick and window layers. The author believes it would have been beneficial to attempt calibration and validation using a individual zone temperatures and heat energy delivery, to make this a more realistic study, even though the statistics provided very low results according to the widely accepted ASHRAE guidelines.

It will be demonstrated in the following sections that these kinds of calibration/validation studies can lead to a goodness of fit that appears statistically sound, but in fact may not be representative of reality, especially when investigating individual zone components of a building. This is equally important for both investigating temperatures and heating energy delivery per zone, though understandably can be difficult in some cases for gas operated systems, requiring disaggregation (e.g. radiator surface temperatures is one potential solution, but previously not considered). There are as yet no studies that look at both, with the particular study in this thesis at an advantage by using a custom BEMS electrically monitored heating system.

5.5 Performing the Automated Calibration

The objective of this section is to outline the steps an automated calibration to determine the glasswool thickness of the external and internal wall construction. Some further assumptions will be made relating to parameter uncertainty. The procedure to calibrate the model will involve iteratively adapting the thickness of insulation (glasswool) using a range of values generated from Latin Hypercube Stratified (LHS) sampling. A range of 10mm - 90mm was chosen, noting that these could fall within a typical range of glasswool insulation thickness, though in fact is outside the range of the actual model, which has a value of 100mm specified. This range was chosen as an example of parameter uncertainty, to further demonstrate how calibration techniques can (wrongly) lead to a solution. LHS ensures a good spread of input parameters (Figure 5.2). 20 samples were generated for each internal and external parameter using LHS sampling, to be iterated through a "for loop" (resulting in 400 simulation runs for each period). A study on uncertainty analysis by Macdonald (2009) indicated that the LHS method, compared to random sampling and stratified sampling, is more robust and leads to less variance.

Simulation runs have been automated to run sequentially. During each run, the ESP-r input files for the wall constructions are modified and fed as new input to each simulation. The output of the simulation is then compared against the measured period and processed for goodness of fit and computes the CV(RMSE) for temperature and energy response. The results are then stored in an SQLite database.

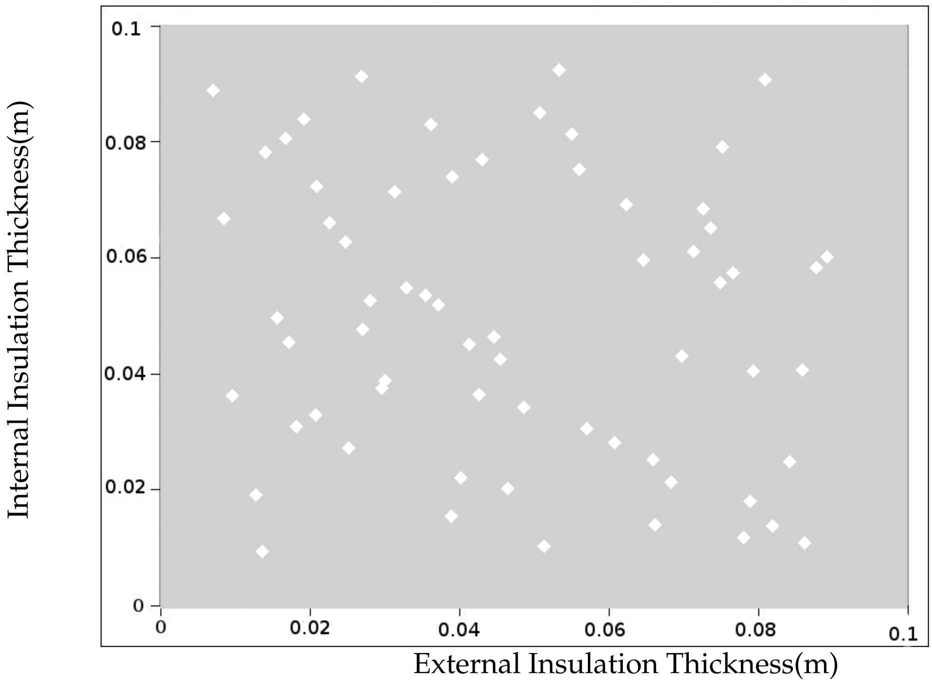

Figure 5.2: LHS Stratification ensures a good spread of values

5.5.1 Initial Setup

1. Process climate data, by extracting temperature, humidity and solar radiation, and prepare as hourly temporal input file for ESP-r for the specified period.

2. Process measured room data, by extracting temperature and heating energy from the BEMS database (RRDtool), and convert to hourly period CSV files.

3. Create LHS hypercube stratified sampling parameters for a thickness between 10mm and 90mm for both external and internal walls.

4. Create calibration SQLite database (used to store data and query for calibration metrics).

5.5.2 Automated Calibration Steps

1. Adapt the ESP-r database with external and internal LHS sample.
2. Carry out simulation.
3. Prepare CSV files for simulated and observed data for comparison in the specified period.
4. Correlate between the simulated and observed data, and record CV(RMSE) for both energy and temperature to SQLite database.
5. Repeat through LHS matrix.
6. Once complete, query database for parameters with lowest CV(RMSE), and extract data for visualising 3D surface plots.

The following sections will present the climate set generated from the weather station data which is input into the simulator and used for the pre-calibration case with assumed definitions of insulation, followed by the results of the calibration procedure.

5.6 Climate Data Set

ESP-r has a climate module to input data from measured sources using a facility called TDF. TDF was used to create a climate data set using data from the BEMS, by processing the BEMS database for temperature, humidity and solar radiation into comma separated value (CSV) files. For the uncertain model, wind data is ignored, since an airflow model was not applied. Climate data of interest are shown in Figure 5.3 for temperature and Figure 5.4 for solar processes.

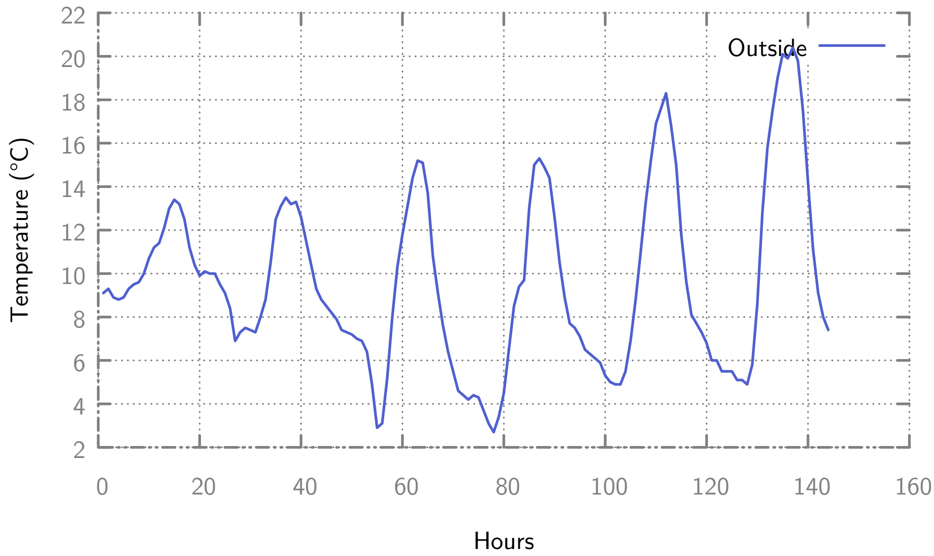

Figure 5.3: External Temperature : March 20th-25th 2012

Figure 5.3 shows the external temperature profile for the climate data set used for the calibration, during the period of 20th - 25th March 2012. Here the peak temperatures can be seen gradually increasing each day, with the lowest temperature recorded at 3°C on the third day (~72 hours) and the highest temperature on the last day at 20°C (~135 hours). The final two days represent Saturday and Sunday, when the heating system has been scheduled to be off.

Figure 5.4 shows the solar processes of the climate data set, during the period of 20th - 25th March 2012, input as direct solar radiation into the BEPS. The range of peak solar radiation varies between 200 W/m^2 (as observed on the first day) to 400 W/m^2 (as observed on the second day).

5.7 Calibration Results

This section shall present the goodness of fit results (graphically and statistically for the calibration (before and after).

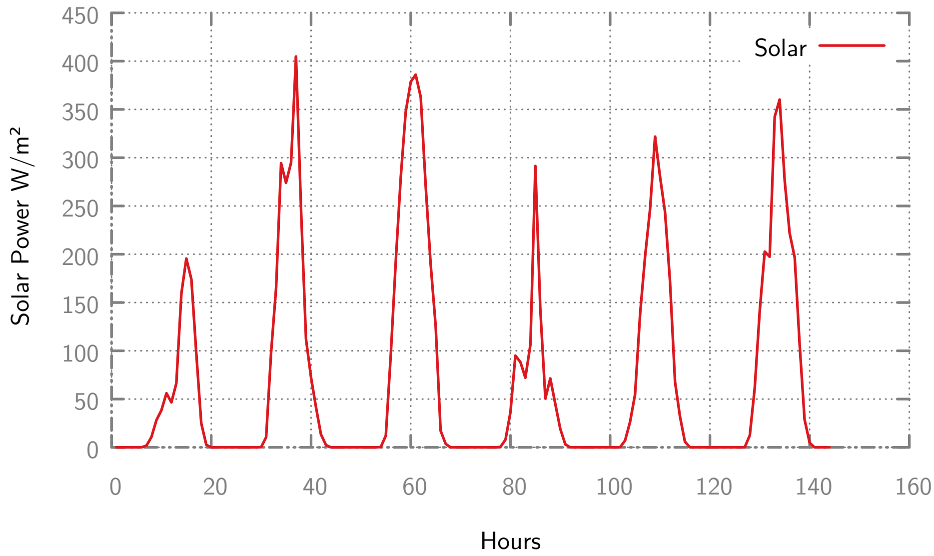

Figure 5.4: Solar Power : March 20th-25th 2012

The base case simulation is based on the initial values for the wall constructions (20mm wool external, 12mm wool internal) as the starting point for the calibration.

Figure 5.5 shows the simulated and measured data with a CV(RMSE) of 14.8%, which is acceptable according to ASHRAE guidelines, which requires models to be under 30%. If we recall back to Coakley *et al.* (2014), who claimed that multiple models could appear calibrated according to the guidelines, this would actually appear to be the case (if only considering temperature evaluation). Days one - four (0 to 100 hours), represent the weekdays, showing the scheduling of the heater from 6am to 5pm to maintain a heating setpoint of 19.3°C. The last two days represent the weekend when the heater was off and temperature variations are due to the external climate only.

Temperatures which rise above the setpoint of 19.3°C can be attributed to solar gains as seen in Figure 5.4, and an increase in external ambient temperature, shown in Figure 5.3. In this case, the simulator does not adequately represent

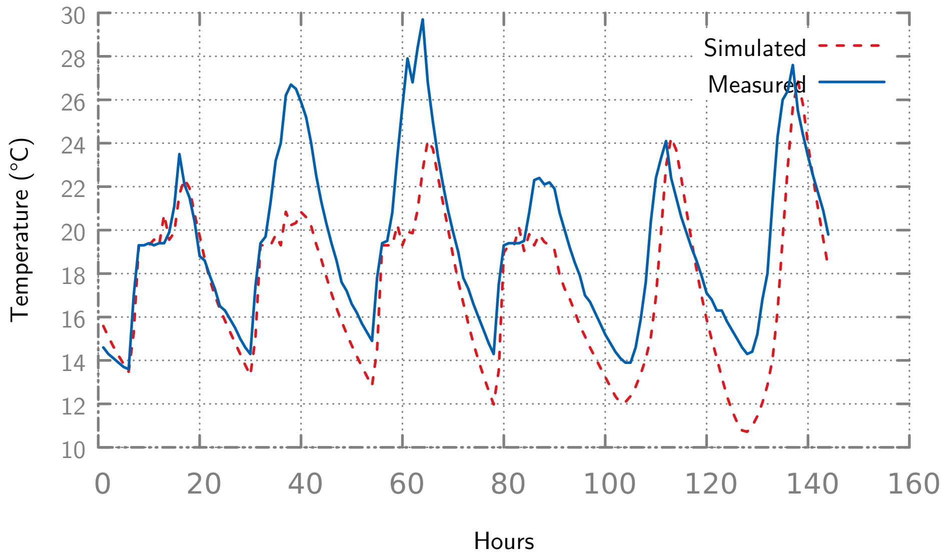

Figure 5.5: Temperature : Base Case : March 20th-25th 2012 : Garage, Setpoint 19.3°C.[Original Database values, 20mm wool external,12mm wool internal]

this phenomenon for days two and three, though there is good agreement for day one. For this particular day, the rise in temperature is closely matched with an identical gradient for both measured and simulated data, as the heating system is actuated to reach a setpoint of 19.3°C. The setpoint is maintained until midday, when the temperature rises steeply due to external gains. The simulator represents this phenomenon, matching the measured well, along with the drop in temperature. However this is not the case for subsequent days, where the measured data shows temperature peaks reaching nearly 30°C on the third day, and gradient drops in temperature that are slightly steeper. The last two weekend days do follow the trend of the measured data reasonably well, but the simulator again drops to a lower temperature by as much as 3°C by the sixth day.

Figure 5.6 shows the measured and simulated data with a CV(RMSE) that is very high at 439%, which is significantly outwith ASHRAE guidelines. The simulated values demonstrate that the model heater is having to work harder to maintain a setpoint, with repeated hourly actuations.

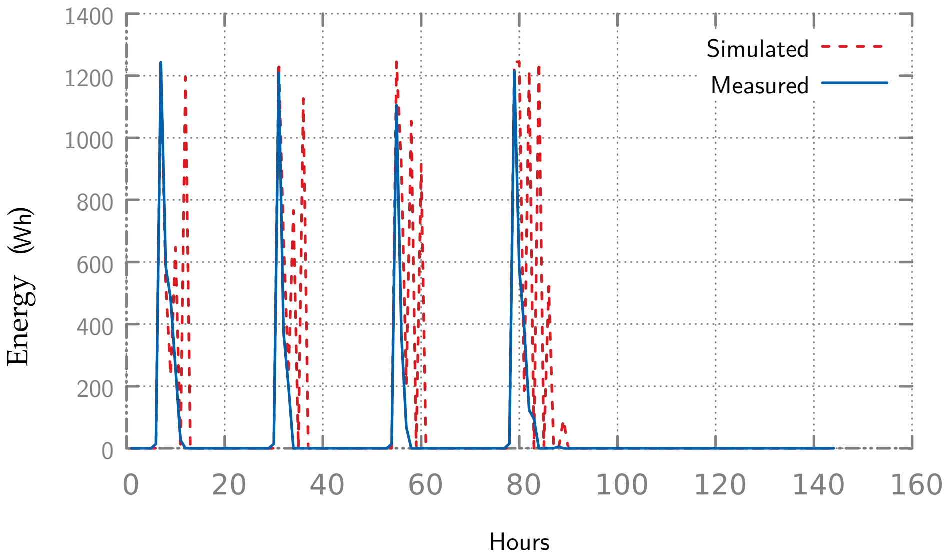

Figure 5.6: Heat Energy : Base Case : March 20th-25th 2012 : Garage, Setpoint 19.3°C.[Original Database values, 20mm wool external,12mm wool internal]

5.7.1 Calibrating for the Lowest CV(RMSE) for Energy Consumption

Since the CV(RMSE) for the base case temperature response is within ASHRAE guidelines, calibration on energy consumption will be explored, in an attempt to lower it towards an acceptable level.

The surface plot shown in Figure 5.7 shows the results of the calibration run for the automated calculations of CV(RMSE) for energy consumption of the Garage heater and depicts the relationship between the CV(RMSE) and glasswool internal and external thickness. The highest error occurs with the lowest amounts of glasswool internal and external thickness. The plot is

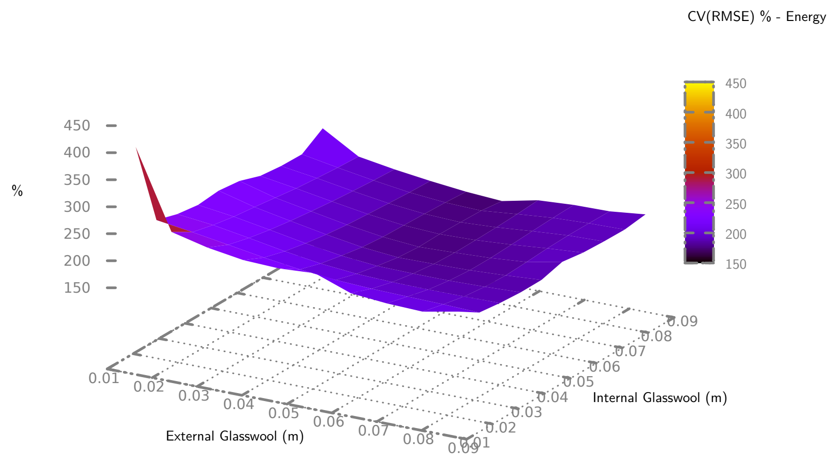

Figure 5.7: 3D Surface plot : Calibration Period : March 20th-25th 2012 : Garage, Setpoint 19.3°C.

largely flat indicating the tuning of these parameters is overall ineffective. The results of the calibration give a CV(RMSE) for energy and temperature at 135.86% and 12.1% respectively. This revises the external insulation glasswool thickness = 59mm and internal insulation thickness = 59mm.

Figure 5.8 shows the measured and simulated temperature data when the model is set to these parameters. Simulated values now follow the trend of the measured data much more closely, with the 2.7% improvement in CV(RMSE) for temperature compared to the pre-calibration case. In particular, the solar gains affecting the model is more evident with the model demonstrating overheating curves that closely match the measured trends. However looking at the first day, the simulator is demonstrating higher sensitivity to overheating compared to the previous pre-calibration case. In subsequent days though the simulator represents the overheating phenomenon more closely; in particular day three reaches peak temperature to within 1°C (though the rise in temperature is delayed by several hours). Day four's simulated profile is almost a perfect match to the measured data, with the simulated overheating occurring at the same time, and a gradient drop in temperature that is near identical. The following two weekend days are also closely matched, though the simulator's rise in temperature is slightly delayed in comparison.

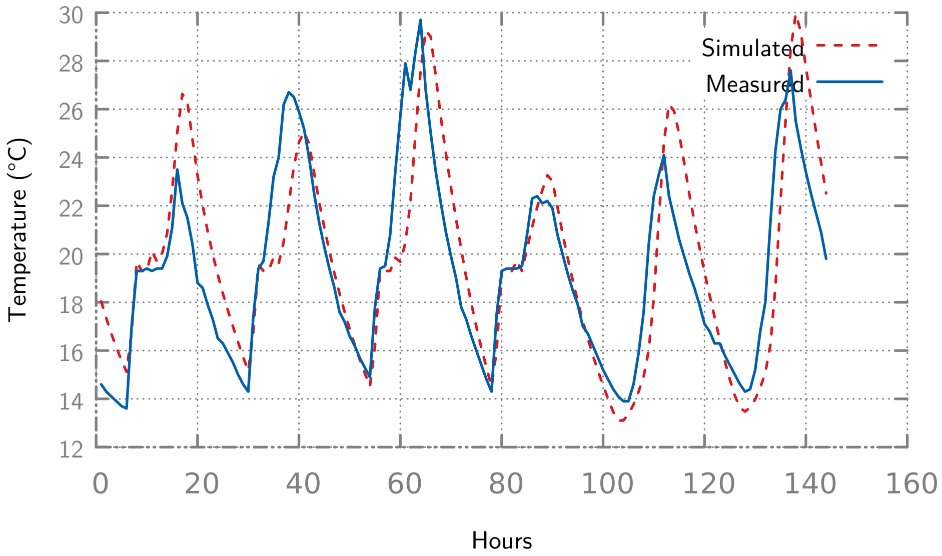

Figure 5.8: Temperature : Calibration Period : March 20th-25th 2012 : Garage, Setpoint 19.3°C.[Calibrated Database values, 59mm wool external,59mm wool internal]

Though 135% is a high CV(RMSE) for energy response, compared to the ASHRAE guidelines, the load profile of the simulated values is consistent with the measured data, as shown in Figure 5.9.

Here the limitation of performing calibration based on CV(RMSE) as per guidelines, at the hourly level for electrical heating loads, is evident. However the CV(RMSE) for temperature response yields a low 12.1% for CV(RMSE), which is well within the guidelines.

Following a potentially well matched initial load profile as seen in Figure 5.9 and Figure 5.8, the heating works the hardest first thing each morning to reach setpoint, but later actuations can significantly vary between time periods.

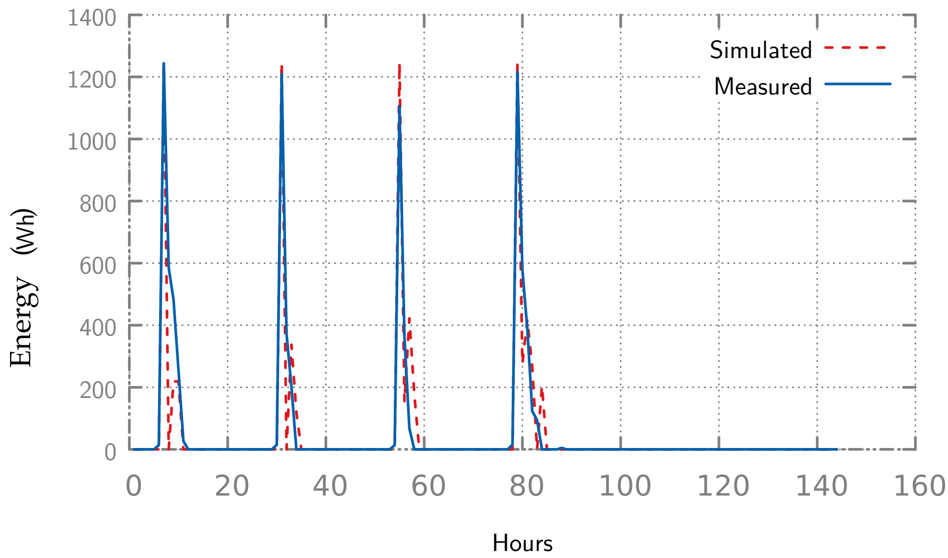

Figure 5.9: Heat Energy : Calibration Period : March 20th-25th 2012 : Garage, Setpoint 19.3°C.[Calibrated Database values, 59mm wool external,59mm wool internal]

Clearly this due to the fact CV(RMSE) compares predicted with measured data point to point, which may be appropriate for hourly temperatures but not highly variable energy delivery. Ruiz Flores and Lemort (2014) also recognise that evaluating calibration accuracy at small time scales (or scales where conditions are very variable) using CV(RMSE) is not appropriate.

Graphically and statistically, the simulated temperature profile of this room could suggest this model is calibrated. In previous calibration studies, such as those carried out by Tahmasebi *et al.*, who only considered a subset of the building and an averaged zone temperature profile for a single floor of a building, a match can indeed be attained to the measured data, however this may not be the case when taking a wider view across the whole building - the effects of ceiling and floor dynamics must also be considered. Furthermore, graphical analysis is equally important, particularly for temperature response, since a small change in CV(RMSE) can actually lead to a significantly better fit to the measured data when shown graphically against the simulator.

The importance of considering whole house dynamics is highlighted by looking at the adjacent Family Room. Figure 5.10 shows the hourly measured v simulated temperature data with the chosen calibrated values, and demonstrates how the uncertain model is failing at predicting the temperature response for this zone.

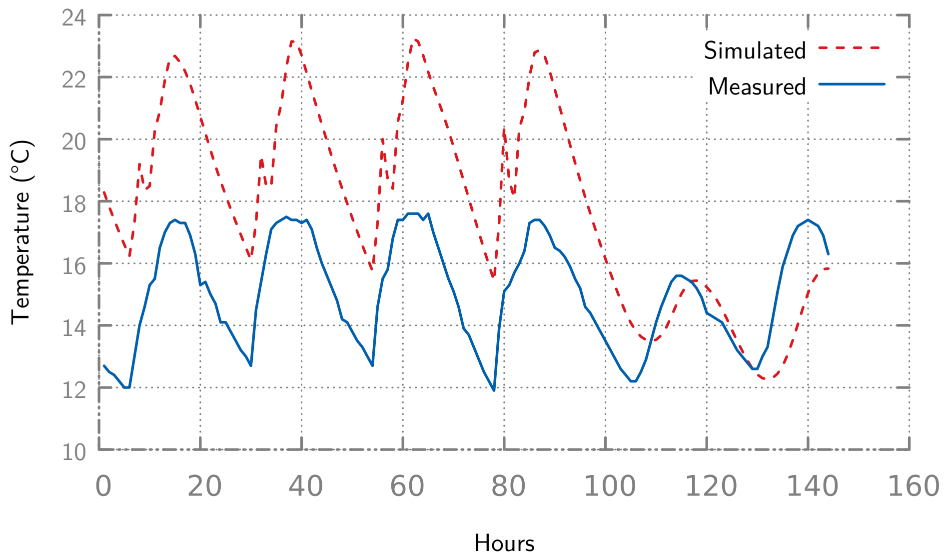

Figure 5.10: Temperature : Calibration Period : March 20th-25th 2012 : Family Room, Setpoint 17.3°C.[Calibrated Database values, 59mm wool external,59mm wool internal]

Figure 5.10 shows a large disparity between the temperatures of the measured and simulated values by as much as 6°C. The simulator is consistently overheating the zone, suggesting that there may be issues with heat transfer, as it appears the heat is not escaping sufficiently to allow the temperature to equalise to setpoint.

Furthermore, in terms of energy response shown in Figure 5.11, the measured values indicate that the heating remains on for the duration of the day, thus showing the heater having to work harder to maintain setpoint. In contrast though, the simulator heat load is minor in comparison, though the simulator temperature response indicates significant overheating, further demonstrating how ineffective the uncertain model is, since it is using a fraction of energy compared to what was measured.

As for modelling uncertainty, airflow has not been considered. This could lead a modeller to apply ESP-r's standard scheduled airflow technique in an attempt to 'force' heat transfer. An example of this is shown in Figure 5.12 with the application of a scheduled airflow rate of 2.5 ACH. This results in the simulator temperature response being more erratic, though the differences between peak temperatures between the simulated and measured data reduced. There could be a temptation to further manipulate the ACH rate in the absence of an air flow model, but this would certainly lead to a model far removed from reality.

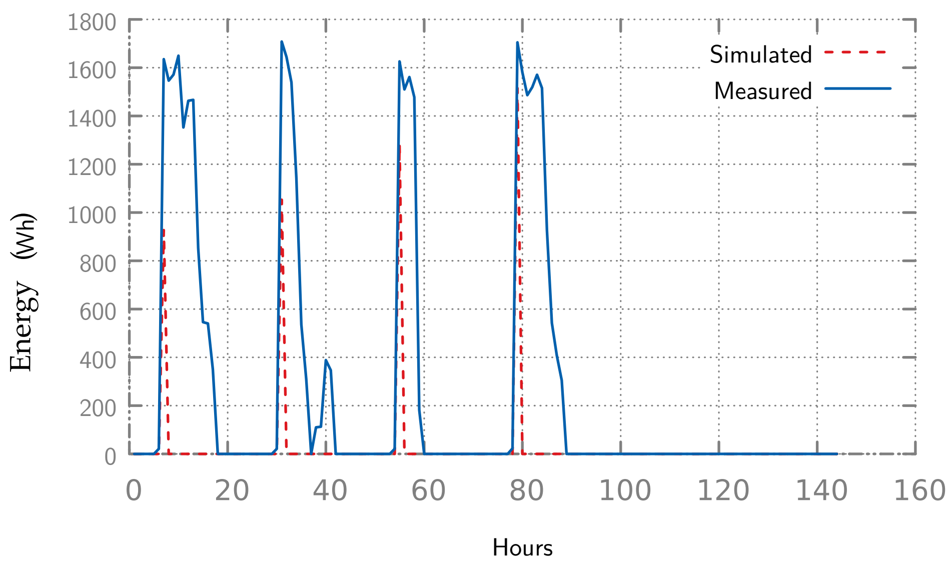

Figure 5.11: Heat Energy : Calibration Period : March 20th-25th 2012. Family Room, Setpoint 17.3°C.[Calibrated Database values, 59mm wool external,59mm wool internal]

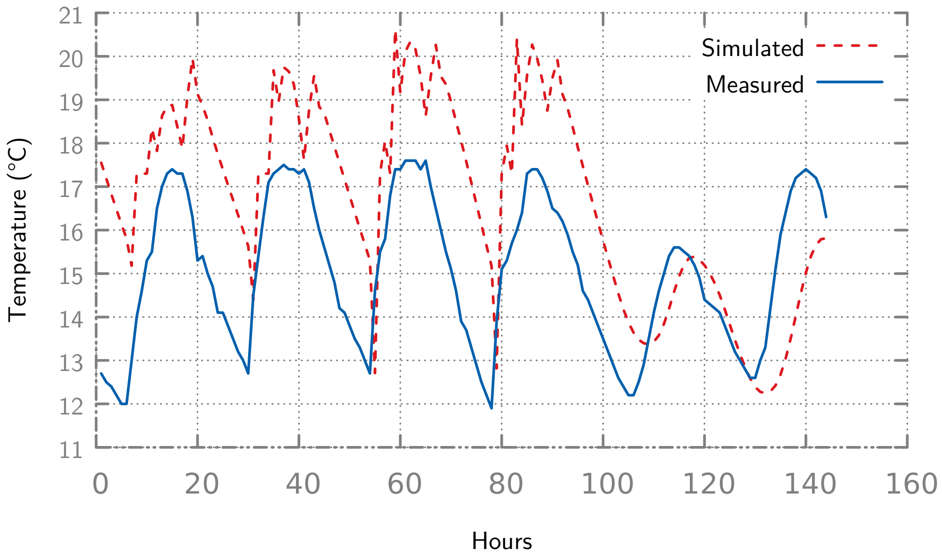

Figure 5.12: Temperature : Calibration Period : March 20th-25th 2012 : Family Room, Setpoint 17.3°C.[Calibrated Database values, 59mm wool external,59mm wool internal] 2.5 airchanges/hour

5.8 Summary

Due to the complexity of interactions in a building model, calibration should only be used to determine a few uncertain parameters. In particular when applying ASHRAE guidelines for temperature fit, a model may appear calibrated when looking at the temperature response of an individual zone, but may not be the case upon deeper investigation of other zones.

The uncertain model makes some assumptions on the structure of the house. The most prevalent assumption, is that there is no roof zone, which has been approximated as an external boundary. There is uncertainty in the choice of unknown parameters (insulation thickness), which can lead to a fit to the data, even if they are out of the actual range (maximum end of range chosen to be 90mm, whereas the actual was 100mm). Finally in terms of modelling uncertainty, a simplified approach to introducing airflow has been applied to investigate if the characteristics can be improved, which can be seen as attempt at ’fudging’, and not conducive to produce a reasonable solution. The problem with this model is most apparent when observing the large disparity in temperature and energy response contained in the the Family Room results, and demonstrates some of pitfalls when relying on calibration to try and achieve goodness of fit to tune the model. A satisfying solution may be achieved for one zone in the model, as can be seen with the high goodness of fit with the temperature response in the Garage zone, but on closer inspection, may not be the case in other zones, as shown in the Family Room zone results. Furthermore, the difficulty with calibrating on energy use when using electrical heating power has been demonstrated, and that CV(RMSE) may not be the most ideal metric to ascertain ’goodness of fit’, when doing hourly comparisons of heat delivery. Though it may be possible to further adjust parameters on the model to achieve a better fit, and may not necessarily represent reality, and therefore may not be able to predict adequately when presented with other data sets and use cases.

Chapter 6

Building Model Validation

6.1 Introduction

This chapter will present the assessment of the goodness of fit for the complete model presented in Chapter 4 to determine the validity for BIM based simulation assisted control. Compared to the model presented in the previous chapter, the model presented here assumes as much detailed information as possible, with minimum uncertainty. However, in terms of the wall constructions, the model still required minor calibration, to ascertain the density of glasswool in the external wall construction, as this could not be ascertained from any Enemetric documentation. Other than this, the model to be assessed has had no further calibration, and simply uses the supplied information for geometry, materials and building operation, as is.

A whole building approach will be taken when determining the goodness of fit using CV(RMSE). This approach computes the total CV(RMSE) for the whole house based on the average CV(RMSE) for both the hourly temperature and energy of the individual room zones which were monitored by the BEMS. Similarly it will be expressed as a percentage.

Another metric which can be used to determine goodness of fit is the Pearson correlation coefficient (Equation 6.1) which can determine how well measured and simulated values correlate in a particular period. It is also expressed as a percentage, whereby the higher the value the better the fit the simulated data is to the measured. For example 100% would yield a one to one match between the measured and simulated data.

$$r = \frac{\Sigma(m_i - \bar{m})(s_i - \bar{s})}{\sqrt{\Sigma(m_i - \bar{m})^2 \Sigma(s_i - \bar{s})^2}} \tag{6.1}$$

6.2 Validation Data Sets

When using the whole house approach during validation to determine goodness of fit between simulated and measured data for all monitored zones, consistent BEMS scheduled operations which can be replicated in the BEPS are required. Since the building was a residential type of house with zoned heating - individual room control was provided to the occupants and Enemetric to test and demonstrate the functionality, and further emulate smart heating control operation. This was provided by the BEMS user interfaces, which allowed manipulation of the setting of zone temperatures in heated rooms as shown in Chapter 3. This differs from control in larger buildings, often used in other building simulation calibration and validation studies, which tend to have non-varying constant setpoints throughout multiple zones, and heating delivered using a gas fired HVAC system. Consequently there is an additional challenge in ensuring setpoints in the three rooms remain constant throughout the validation periods. As part of the BEMS monitoring facility all setpoints were tracked throughout the year to identify periods which could be used for simulation. There also needs to be consistency in the measurements, with no gaps in the data collection (e.g. due to sensor error) or occasions of BEMS malfunctioning. An example of a BEMS malfunction and irregular setpoint control is shown in Figure 6.1 .

6.2.1 Control Errors in BEMS dataset

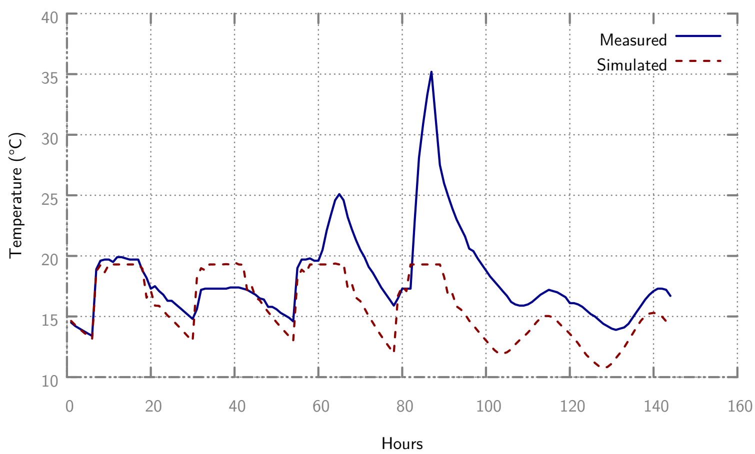

Figure 6.1: Temperature : Base Case : March 20th-25th 2012 : Master Bedroom with BEMS control malfunction

Figure 6.1 shows the Master Bedroom measured data and simulation results for the period March 20th-25th 2012, which was the period presented in the last chapter. The BEPS model's control file has been set to actuate the heating with a 19.3°C setpoint for the simulation period. On the first day (0-24 hours), there is perfect agreement with both measured and simulated data showing the same gradient and rise of temperature to the setpoint of 19.3°C. However, the second day (24-48 hours) of the measured data shows a change to a reduced setpoint, with the setpoint returning to 19.3°C on the third day (48-72 hours). Most notable are the two peak temperatures on the third day and fourth day (72-96 hours), where it appears the BEMS has lost control of the heating system, and is unable to turn the heater off. This is most evident with the peak temperature of 35°C on the fourth day.

6.2.2 Validation Periods

Taking into account the above, validation periods (Figure 6.2) need to have consistent data, which can therefore be replicated in the simulator, and also varied to consider different times of the year, to test seasonal validity of the BEPS model.

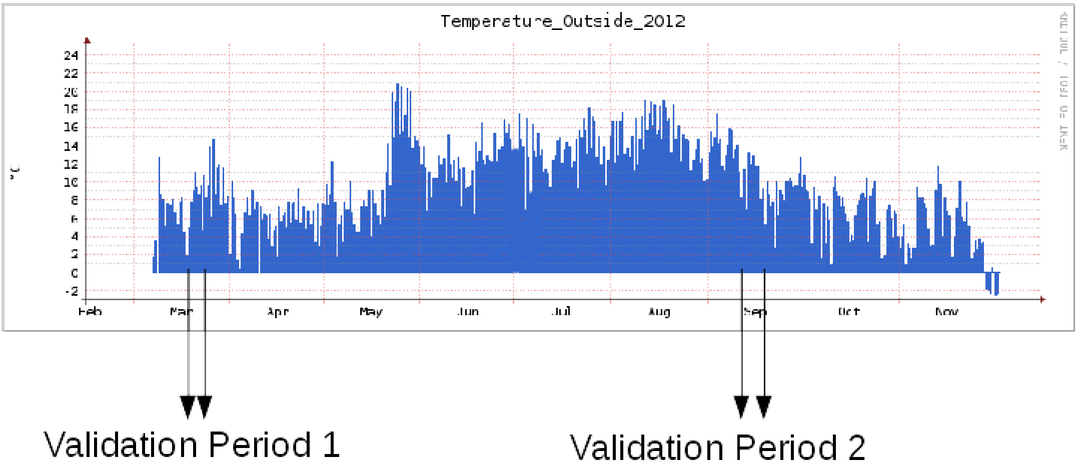

Figure 6.2: Validation Periods

Two periods have been identified that meet these requirements.

1. 15th - 20th March 2012

2. 10th - 17th September 2012

6.3 Minor Calibration to determine density of glasswool in external wall

The only uncertain parameter was the density of the glasswool for the external wall. The calibration steps presented in Chapter 5 were adapted to determine this density. The range of densities were specified between 10 - 250kg/m^3, and the calibration was automated in step increments of 10kg/m^3 to modify the materials database file using the March climate dataset to find the combined lowest whole house average CV(RMSE) for temperature and energy. This yielded a density of 190kg/m^3.

6.4 Validation for Goodness of Fit

This section will present the goodness of fit statistics for the whole house model presented in Chapter 4. It must be noted that this model has only had a minor calibration of glasswool density, with all other parameters derived from Enemetric information (materials, geometry) and the BEMS (operations), with no modification (equivalent to data provided from a BIM). As such, this section also represents a validation study for ESP-r's prediction capabilities for a BIM derivative model. This model will also utilise a full climate data set for March and September, including wind speed and direction, required for airflow modelling. Since the wind speed and direction data was not measured by the BEMS weather station, it has been downloaded from a station located very close to the site of the house. (Weather Underground (WU) Station location - 55.78 °N, 3.93 °W (Elevation - 121 m); House location - 55.77°N, 3.93 °W).This weather station's temperature was verified with the BEMS weather station temperature sensor shown in Figure 6.4 (at the rear of the house, away from direct sunlight) to ensure the time period was synchronised, and also representative of the location. The graph is depicted in Figure 6.3, and appears well matched. The full set of climate data used for March and September is in Appendix A & B.

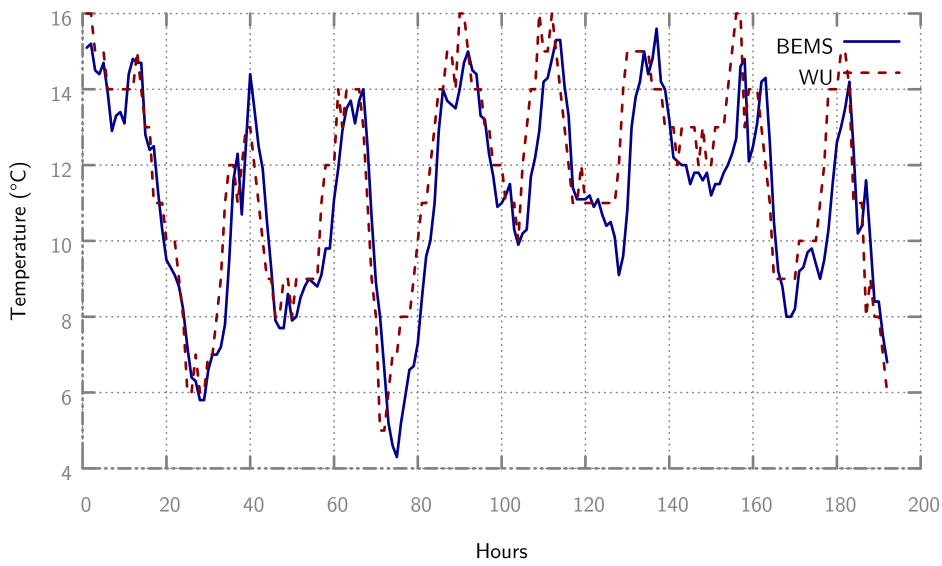

Figure 6.3: External Temperature from BEMS and Weather Underground (WU): September 10th - 17th 2012

The tables of goodness of fit statistics will be presented first, followed by further discussion of the predictions made by the simulator by comparing measured and simulated temperature and heat energy load profiles for various rooms across the two time periods.

Table 6.1 shows the goodness of fit statistics for each zone in the model using the March dataset. The average CV(RMSE) for the whole house is computed to be 11.5% with the individual CV(RMSE) for the Garage and all Bedrooms under 10%. The lowest individual CV(RMSE) is calculated to be for the Garage zone at 7.3%. The Master Bedroom has the highest Pearson correlation at 95%. Table 6.2 shows the goodness of fit statistics for each zone in the model using the September dataset. The average CV(RMSE) for the whole

Figure 6.4: External Temperature Sensor at Rear of House

house is computed to be 8.6%, which is lower than March, with the individual CV(RMSE) for all zones under 12%. However the Pearson correlations are lower than those computed for March, suggesting the prediction capability is not as strong. For example, the lowest individual CV(RMSE) for temperature in this dataset is calculated to be for the Bedroom 2 at 5.85%, but the correlation is 70%. This comparatively low CV(RMSE) is interesting to note, as CV(RMSE) results in shorter time periods (such as March) are penalised more, when they have higher Pearson correlation. The same observation however cannot be said regarding CV(RMSE) for heat energy comparisons.

There are few building simulation calibration/validation studies that look at individual hourly temperature zone CV(RMSE), but these values are competitive against a recent study for a large office building presented in Mustafaraj *et al.* (2014). They attained a range between 12.4% - 28.7% for CV(RMSE) when comparing indoor zone temperatures of measured and simulated data. Overall the results also show that the model is well within

Zone	CV(RMSE)(%)	Pearson (%)
Garage	7.3	93
Family Room	12.8	80
Kitchen	17.7	87
Bedroom 2	8.8	78
Bedroom 3	8.9	73
Master Bedroom	9.6	95

Table 6.1: CV(RMSE) & Pearson Correlation for Individual Zone Hourly Temperatures (March Dataset)

Zone	CV(RMSE)(%)	Pearson (%)
Garage	11	83
Family Room	8.88	56
Kitchen	7.52	85
Bedroom 2	5.85	70
Bedroom 3	11.6	63
Master Bedroom	8.09	69

Table 6.2: CV(RMSE) & Pearson Correlation for Individual Zone Hourly Temperatures (September Dataset)

the ASHRAE guidelines when considering goodness of fit using hourly temperature comparisons, which requires a CV(RMSE) of less than 30%.

Table 6.3 and Table 6.4 show the CV(RMSE) and Pearson correlations for heat energy loads in the March and September datasets. The CV(RMSE) is consistently high for all heating zones in both time periods. As discussed previously, the CV(RMSE) does not appear fit for purpose to ascertain goodness of fit between measured and simulated data for heat energy

Zone	CV(RMSE) (%)	Pearson (%)
Garage	147	87
Family Room	121	72
Master Bedroom	217	87

Table 6.3: CV(RMSE) & Pearson Correlation for Individual Zone Hourly Energy (March dataset)

Zone	CV(RMSE) (%)	Pearson (%)
Garage	161	81
Family Room	161	57
Master Bedroom	173	81

Table 6.4: CV(RMSE) & Pearson Correlation for Individual Zone Hourly Energy (September dataset)

consumption at the hourly detail. This will become apparent, during further discussion of the graphical results of the heat energy loads.

Figure 6.5 presents the hourly measured versus simulated temperature profile for the Garage in March and shows good agreement with a CV(RMSE) of 7.3% and Pearson correlation of 93%. In particular the two weekend days demonstrate natural heating of the space from external gains (e.g. solar radiation through the large French door opening), including an identical peak temperature matched on the third day. On heating days the gradient representing the rise to setpoint on 19.3°C is perfectly matched. It can also be seen that the fall in temperature simulated (i.e. the rate of change in temperature) is also a near perfect match to the measured data. There are minor temperature spike artefacts (sharp rise and decline by 1°C) exhibited in the simulated data that do not match the measured. This is most visible on day two, when the simulated spike occurs before the measured. However the

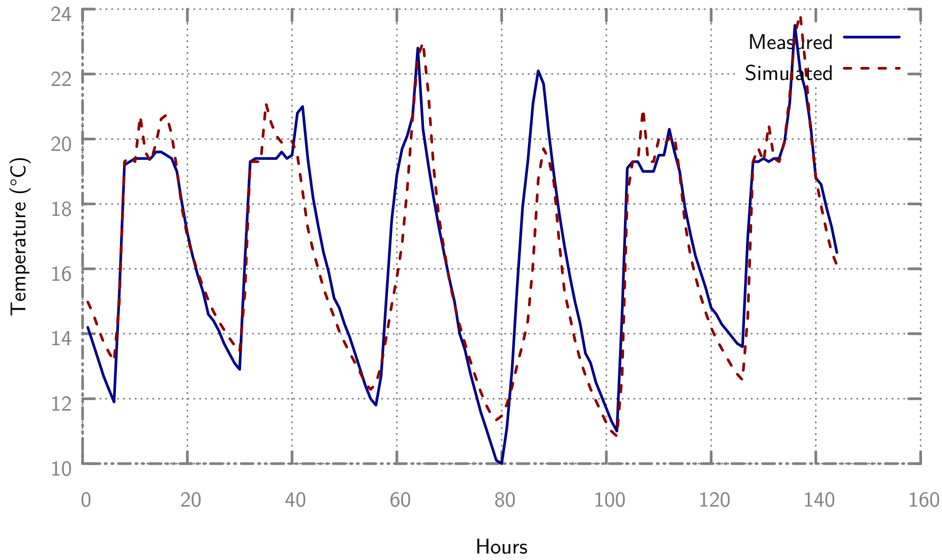

Figure 6.5: Temperature : March 15th - 20th 2012 : Garage, Setpoint 19.3°C.

most prominent spike on the last day appears to be perfectly matched between the simulated and measured data. Overall the simulator appears to predict the temperature and gain response for this zone in this period very accurately.

Figure 6.6 presents the hourly measured versus simulated energy data for the Garage in March and shows that even though, the simulator is consuming slightly more overall energy, the profile and peak loads simulated data are closely within the bounds of the measured data, with a CV(RMSE) of 147% and Pearson correlation of 87%. The additional energy consumed by the simulator used to maintain the setpoint is visible in the spikes that follow the initial maximum heating load on most days. Minor spikes in energy consumption are visible in the measured data (under 200Wh) and only matched on the second day (shown as the small spike later in the day at 40 hours). Though the CV(RMSE) is high compared to the accepted ASHRAE guidelines, graphically it appears that the heating is being simulated with a good degree of accuracy. Once again the problem with using CV(RMSE) for hourly zone heating energy is evident, as comparisons are being made point by point, punishing large

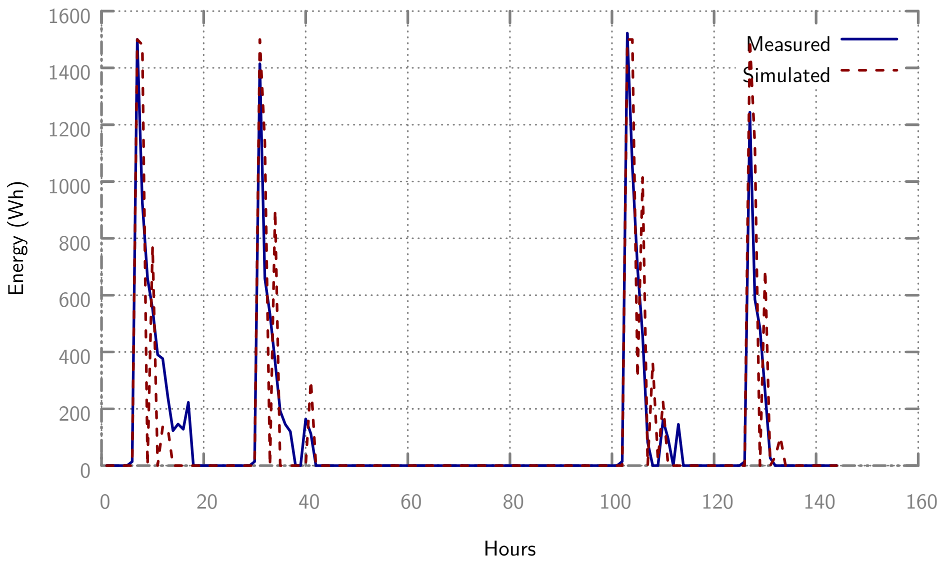

Figure 6.6: Heat Energy: March 15th - 20th 2012 : Garage, Setpoint 19.3°C.

deviations, even though the energy load appears well matched graphically. It can be said that the application of this metric to purely statistically evaluate this component of simulator's accuracy is not fit for purpose, and graphical evaluation should be used, when conducting equivalent studies.

Figure 6.7 presents the hourly measured versus simulated temperature profile for the Garage in September. This dataset represents a full week (Monday - Sunday, 0 - 168 hours), followed by one Monday (168-192 hours). During this period the setpoint was 21.4°C. The CV(RMSE) for this period is 11%, and the Pearson correlation is 83%. Overall the simulated data is following the trend of the measured data, however there are noticeable discrepancies evident by the difference in peak spikes on days two, three, five, six and seven. Looking at Figure B.3 (Appendix B), which shows the solar radiation for the September period, it appears the simulator is processing the solar gain measurements on these days, to exhibit sharper increases in temperature, compared to the measured data. The possible reason for these discrepancies could be due to the solar gain measurement apparatus calibration. To explain this, the incident

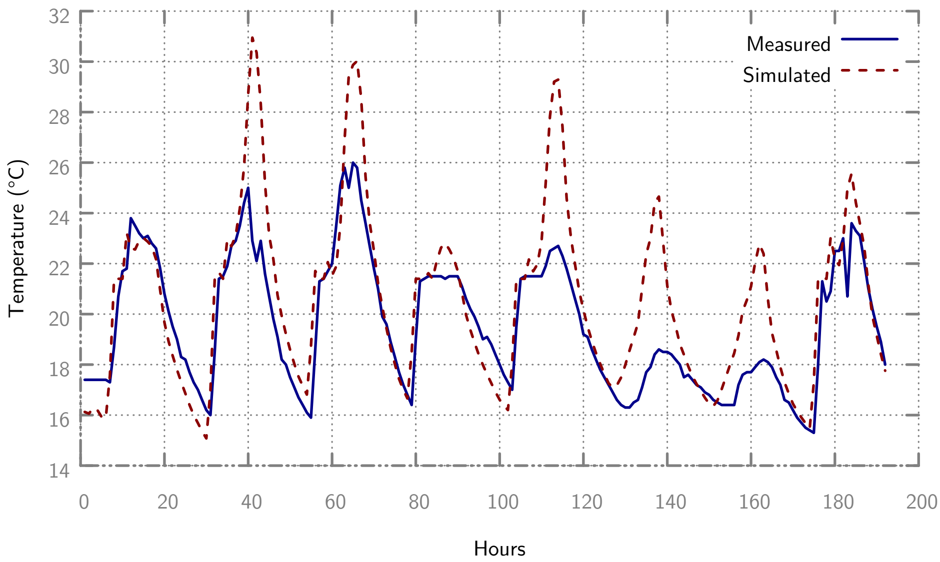

Figure 6.7: Temperature : September 10th - 17th 2012 : Garage, Setpoint 21.4°C.

angle of the sun's solar radiation varies throughout the year, which would have an effect on the measurement accuracy since the solar sensor was only calibrated once.

Apart from these differences due to the solar measurement, there still appears to be a generally good match between the measured and simulated data, with respect to the rise and fall temperature gradients, which appear well aligned on heating days. This is most apparent on day one, three and eight.

Figure 6.8 presents the hourly measured versus simulated energy data for the Garage, in September, with a CV(RMSE) of 161% and Pearson of 81%. Similarly to the March dataset, the simulator appears to be matching the heat load profile of the measured data. For this zone, the majority of heating is carried out in the morning, though there are some heat load spikes which have been measured and not exhibited by the simulator. The most visible of these are at 40 hours and 180 hours. The heating is most active during the morning, with the solar

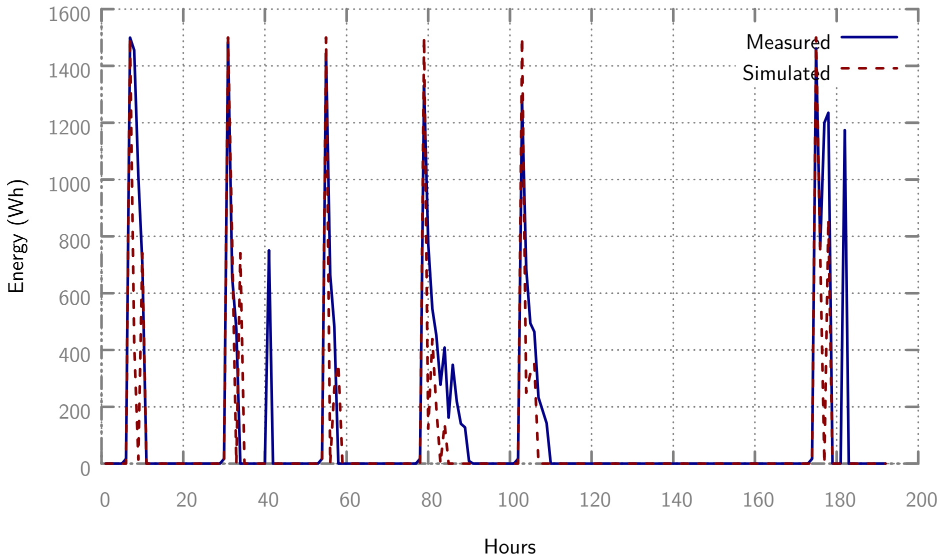

Figure 6.8: Heat Energy : September 10th - 17th 2012 : Garage, Setpoint 21.4°C.

gains later in the days naturally heating the space, and for the most part, the simulator replicates this behaviour in terms of energy load.

In terms of increased solar gains processing Figure 6.9 also demonstrates the same phenomenon for Bedroom 2 in September. This figure shows the hourly measured versus simulated temperature data for the Bedroom 2 zone. Bedroom 2 is situated directly above the Garage, and similarly shows simulated peaks of temperature above the measured due to the solar gains. Aside from these discrepancies the temperature profile appears to match well with a CV(RMSE) of 5.85% and Pearson of 70%, though the simulator exhibits a slight delay for the rise and fall of temperature. This is most apparent on the first day. This could be due to a door being open in reality, whereas in the simulator they are assumed to be closed.

An example of a room not affected by solar gains can be seen in Figure 6.10. This presents the hourly measured versus simulated temperature profile for the Family Room in March. Compared to the results for this room presented in

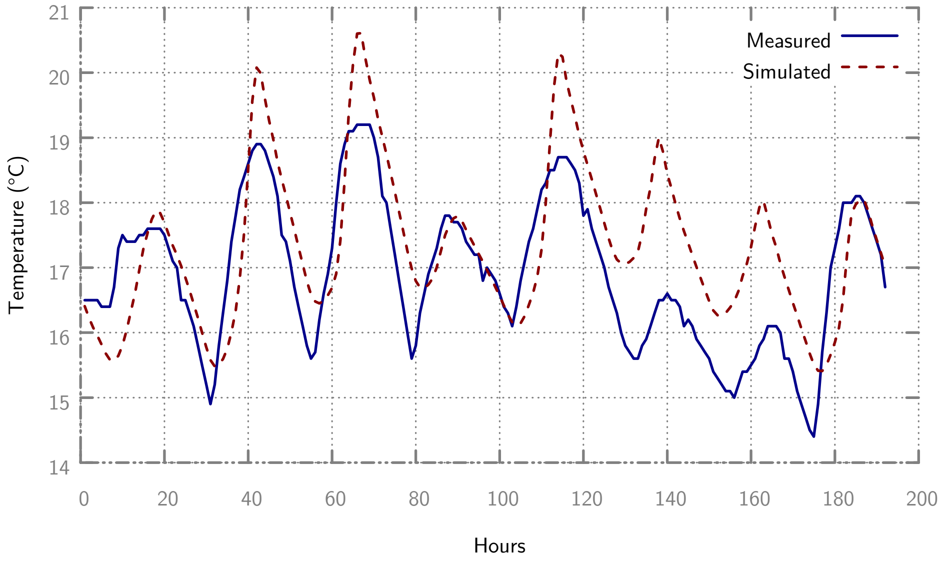

Figure 6.9: Temperature : September 10th - 17th 2012 : Bedroom 2

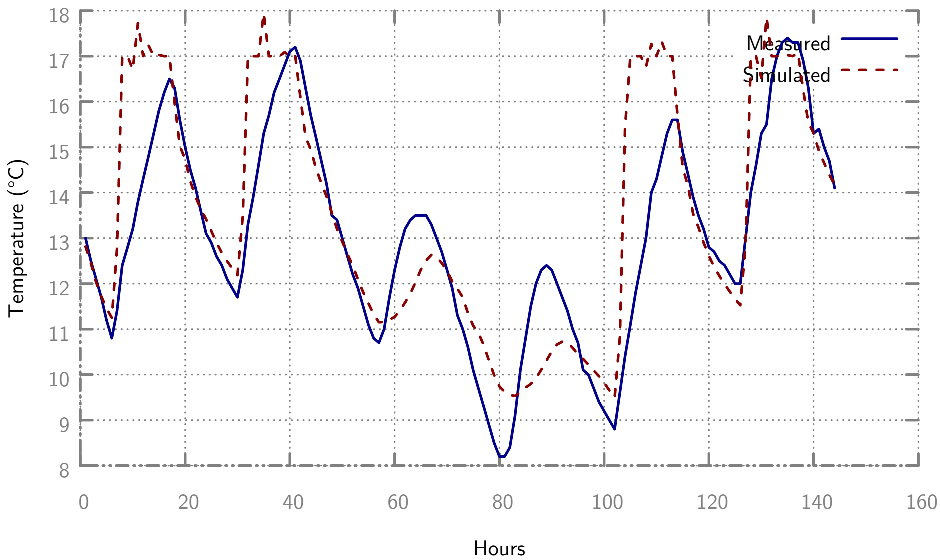

Figure 6.10: Temperature : March 15th - 20th 2012 : Family Room, Setpoint 17.3°C.

the last chapter, which approximated the roof as an external boundary, the full whole house model is being simulated fairly well with a CV(RMSE) of 12.8% and a Pearson correlation of 80%. This was shown in Figure 5.10 where the simulated profile was predicted consistently around 6°C above the measured data. Now this is not the case, with the simulator predicting within the bounds of the measured profile. Clearly, this is due to not approximating the roof and such approximations should be avoided. It could also be concluded that multiple storey buildings should have accurate geometric representation when built for BEPS, and modelling subsets of a building is not going to adequately represent reality, as the thermal capacitive effects of multiple levels of the building must be taken into account.

Looking at the finer details of the measured and simulated profiles, there is a difference in the heat up phases, with the simulator reaching setpoint (almost immediately), compared to the measured data points. However the temperature fall gradient is an almost perfect match on all heating days, showing the simulator losing heat at the same rate as what was measured. The rate of change of decreasing temperature is the same for the simulated and measured profile, therefore the heat loss (output) must also be the same and the thermodynamics of the room is modelled correctly. The physics of this room is interesting as it is contained within an open area, and has fictitious surface relationships with the Kitchen and Stairwell zones, compared to other living area zones, which tend to all have physical boundaries. Looking at the temperature profile it could be concluded that the model is injecting more heat energy, than what was measured. However looking at the heat energy profile in Figure 6.11, the measured heater remained on throughout the duration of the day, almost at maximum heat load capacity. Looking at this figure the simulator appears to consume half of what was measured; whereas the simulated load profile, though showing actuations throughout the day, are not at maximum load. There may have been a problem with this particular heater, as it appears quite inefficient, and looking at the measured data of the temperature profile, could be acting like a heater with a third of the heating capacity. Since the electricity consumption was only measured, and not radiator surface temperatures, it can be difficult to pinpoint the disparity, which could possibly be with the internal control system of the heater. Electrical heaters always have a cut-off mechanism to disable the heating element when the oil has reached a sufficient temperature. This is not accounted for in the simulation.

Though it is possible to model an oil filled radiator using ESP-r, and specify additional properties such as the heat capacity of oil used, it cannot be operated using basic on/off control that was similarly employed in the BEMS. Another possibility is that, there could be significant losses in the conversion of electrical to heat energy of the measured heater. This can be theorised in the simulator. Figure 6.12 shows the hourly measured versus simulated temperature data for the Family Room, when the heating capacity has been arbitrarily reduced to 500W. Here the simulated data now matches the measured data; the gradient rise and fall correlates very well on the first and second day. On the fifth day (a Monday following a weekend of no heating), the simulator similarly does not manage to reach setpoint as the measured data. In conclusion, if the model was to be further calibrated, the heating capacity of the Family Room would be a parameter that could be optimised.

Figure 6.13 presents the hourly measured versus simulated temperature data for the Kitchen in March, with a CV(RMSE) of 17.7%, which is the highest CV(RMSE) for the March dataset. The Kitchen zone is heated via the adjacent Family Room Heater, and the simulator represents the increases in temperature during the heating days. The comparatively high CV(RMSE) is due to two weekend days (three and four) not aligning well between the simulated and

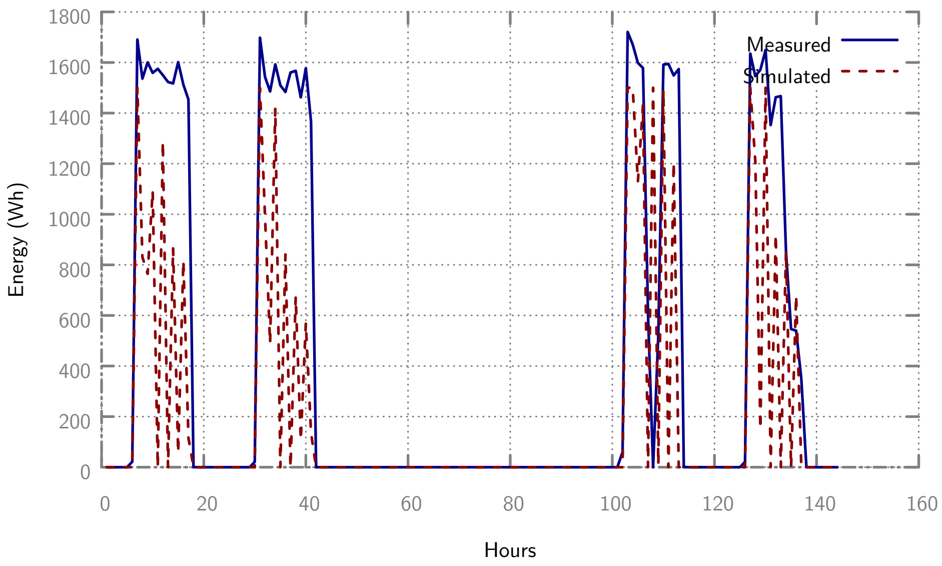

Figure 6.11: Heat Energy : March 15th - 20th 2012 : Family Room, Setpoint 17.3°C.

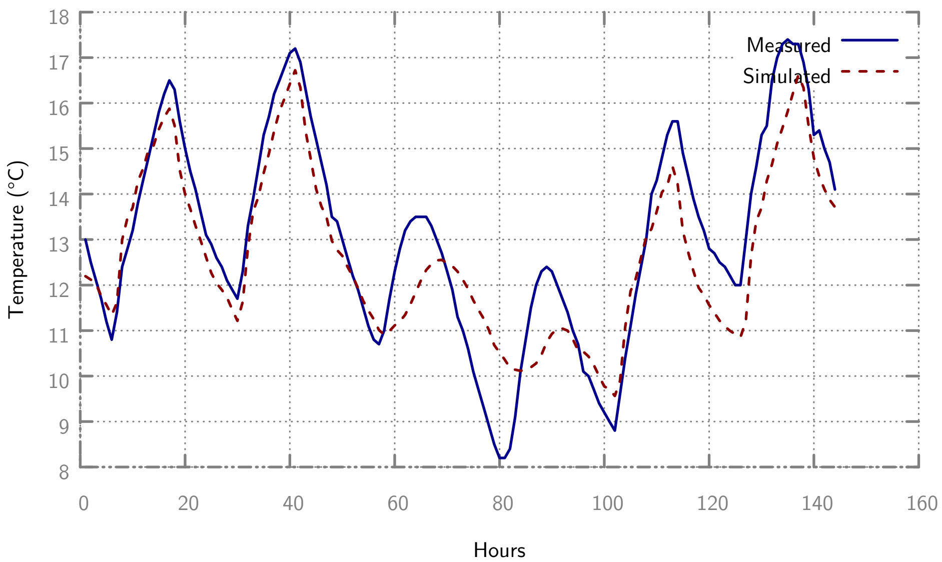

Figure 6.12: Temperature (500W Capacity) : March 15th - 20th 2012 : Family Room, Setpoint 17.3°C.

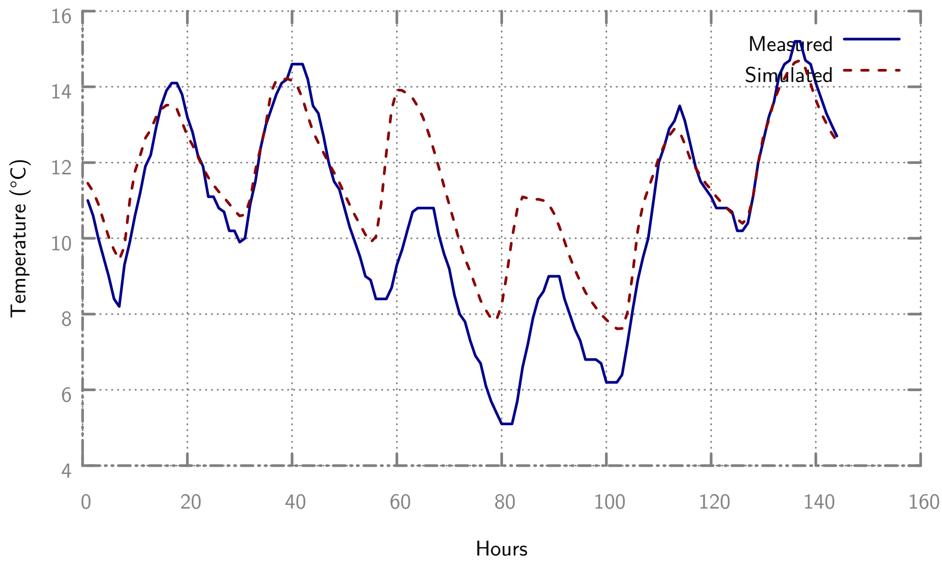

Figure 6.13: Temperature : March 15th - 20th 2012 : Kitchen

measured data points. There is a large difference between the peaks for these two days. It appears as if the model is retaining heat in this zone in comparison to the measured data. This may be an unaccounted for by pressure drop due to the construction of the north façade. If we recall the north façade had no insulation and render, with only an exposed honeycomb layer which is in fact a fully vented panel (shown in Figure 6.4). These panels have many small holes, which would be far too complex to model.

The same phenomenon can also be observed in the September dataset. Figure 6.14 presents the hourly measured versus simulated temperature profile for the Kitchen in September, with a CV(RMSE) of 7.52% and Pearson correlation of 85%. The two weekend days (six, seven) show a 2°C difference between the peak temperatures of the measured and simulated data. However overall during this period the simulator matches the rise and fall of temperature during the week (day one-seven) with good agreement. This is most evident between day three, four and five, where the gradients are perfectly matched.

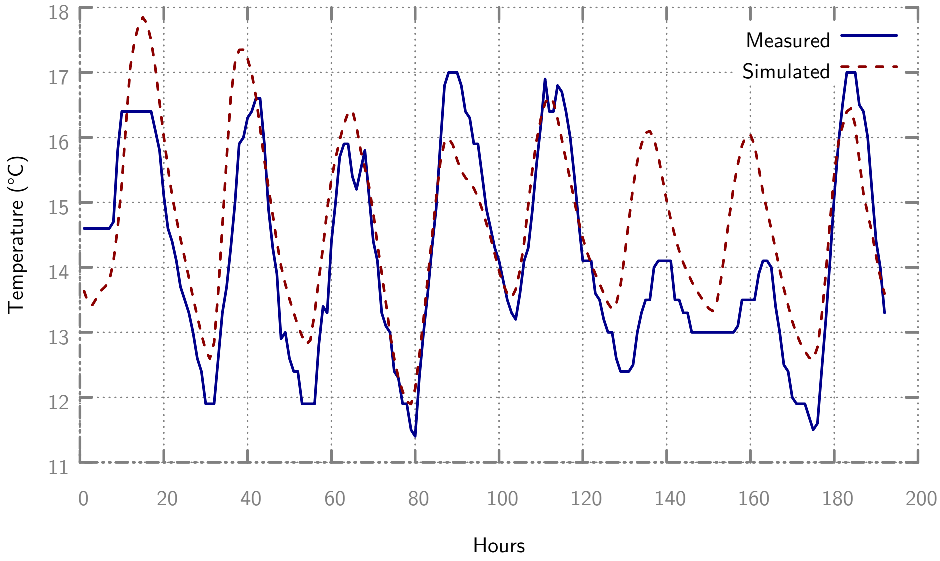

Figure 6.14: Temperature : September 10th - 17th 2012 : Kitchen

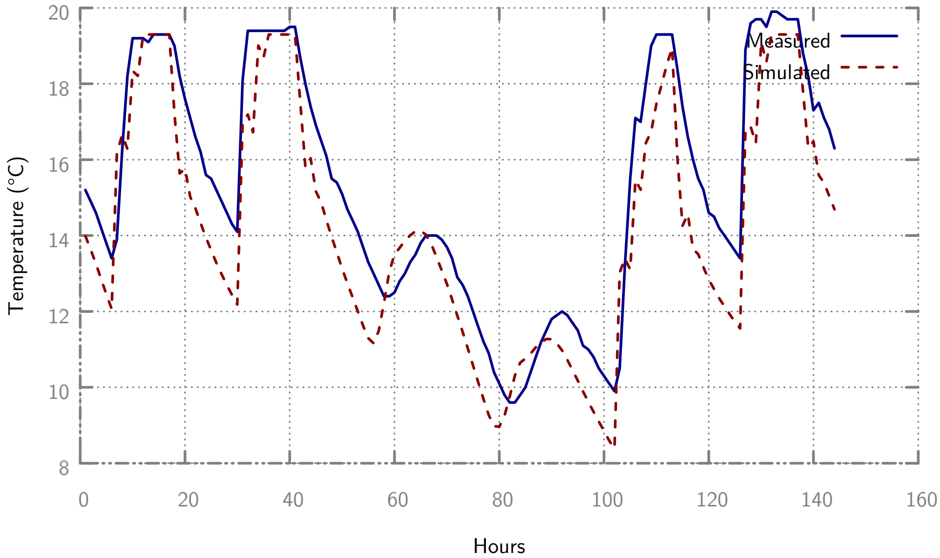

Figure 6.15: Temperature : March 15th - 20th 2012 : Master Bedroom, Setpoint 19.3°C.

Returning back to an example of a heated room, Figure 6.15 shows the hourly measured versus simulated temperature data for the Master Bedroom in March with a CV(RMSE) of 9.6% and Pearson correlation of 95%. The Master Bedroom is the only zone that makes use of an internal boundary surface partition to divide the area with an en-suite toilet.

As can be seen, the simulated temperature profile is fairly well matched with the measured, and follows the trend of the rise in temperature. However the model's rate of change in temperature as it decreases is faster: the gradient drop is steeper in the simulated data, suggesting higher rate of heat loss, as the model cools down to a lower temperature by 2 $^{\circ}$C, on most days. The two weekend unheated days (three, four) show the simulated data matching the profile of the measured, whereas day three shows a higher increase in temperature than day four and with good agreement - with the main difference being the simulator processing the temperature increase sooner than what was measured. This particular difference along with the difference in rate of change of decreasing temperature could be due to the bed in the room (visible in Figure 6.17), which would give the room a higher thermal mass, not accounted for by the simulator.

Figure 6.16 shows the hourly measured versus simulated energy data for the Master Bedroom, with a CV(RMSE) of 217%.The Master Bedroom has an Infranomic branded far infrared mirror heater installed, with a maximum heating capacity of 550W (Figure 6.17). These types of heaters are designed to radiantly heat occupants directly, and such systems are pitched to reduce the amount of heat wasted through infiltration and air movement. Unfortunately this type of heater is not specified in ESP-r, and the simulated energy results do not correlate well with the measured, suggesting further in depth modelling is required to represent the heater's thermal characteristics. In 2013, the Energy Systems Research Unit (ESRU), University of Strathclyde (maintainers

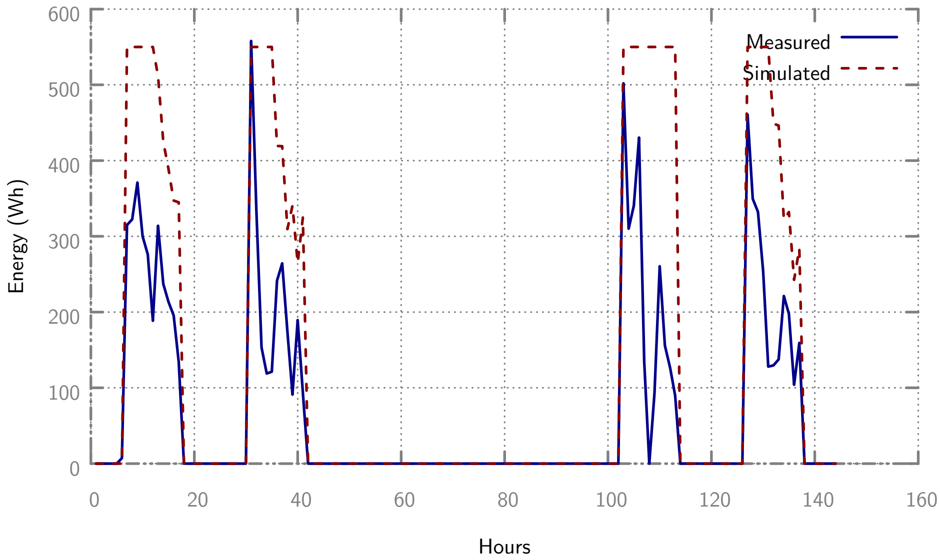

Figure 6.16: Heat Energy : March 15th - 20th 2012 : Master Bedroom, Setpoint 19.3°C.

of ESP-r) carried out a detailed study on Infranomic heaters. The approach they used was interesting, as they modelled the heater as a *zone*. ESRU sourced information about the composition of the infrared panel and adapted the size and characteristics of the initial model to reflect the literature available. The infrared panel is explicitly represented as a separate zone with heat injection into the IR face of the panel but with additional heat losses via the side frame and to the wall face behind the panel. They concluded in their analysis that far infrared panels use 41% less kWh to heat a room than an equivalent modelled electric storage heater, to the same temperatures. This was not an empirical study however, and comparisons of the energy consumed of an actual IR heater with the simulated model were not carried out [Silver (2013)].

Figure 6.17: Far infrared mirror heater.

6.5 Discussion of Validation Results

Modelling the energy input is a challenge as the characteristics of the heaters are difficult to model according to the control strategy implemented in the BEMS. This is most apparent with the Family Room and Master Bedroom heaters and the disparity between the measured electrical consumption and their heat delivery in the maintenance of a setpoint throughout the day. Furthermore, the heater characteristics previously described are not modelled in ESP-r, and are purely represented as heat injecting surfaces with 100% heat energy delivery, not taking into account any further losses in the translation of measured electrical energy to heat energy and the internal control systems of the heaters employing thermal cut-outs in the maintenance of a radiator surface temperature (whereas a zone's sensor and actuator relationship is maintained with a zone air temperature). This is not so much the case with the Garage zone, since the majority of heat load occurs during the morning heat cycle, and the heating system effectively is deactivated later in the day due to the passive solar heating phenomenon. However the processing of solar gains appears to have an increased temperature response in the simulator when using the September dataset. The solar measurement apparatus consisted of a light dependent resistor (LDR) which was calibrated with a lux meter. LDRs vary electrical resistance depending on the light intensity that falls upon it, therefore one possible explanation could be the angle of incident light during this period increasing the intensity outwith the calibration. Maile (2010) made a recommendation in his thesis after conducting a case study for several buildings, stating that more thorough sensor calibration is required when comparing measured and simulated building data, which should be at least every month for solar sensors.

In the model, doors have been assumed to be closed, and therefore unaccounted for in terms of heat transfer, if they have been open in reality; however cracks have been specified for air-flow. An improvement to better understand door usage would be to install door sensors to be monitored which could be monitored by the BEMS.

In terms of validation, it has become repeatedly apparent that the CV(RMSE) metric, when used for hourly heat energy comparisons is unsuitable and it is in fact better to analyse the comparison graphically.

Viewing the daily energy load can also be useful. For example, Figure 6.18 shows the daily energy loads for the Garage heater in March as a bar chart. The loads appear closely matched; in particular the second day is close within 116 Wh.

The main criteria regarding the validation is if building models created for BEPS can be used for predictive control in BEMS. This appears possible when energy delivery and thermal response are shown to be reasonably well matched. Since the control strategy being considered is for optimum heat start up after a long period of heating inactivity, the energy load that is most important is the initial period when the heating is activated. We can evaluate if this strategy can work with the Garage zone, since it has provided the most promising results.

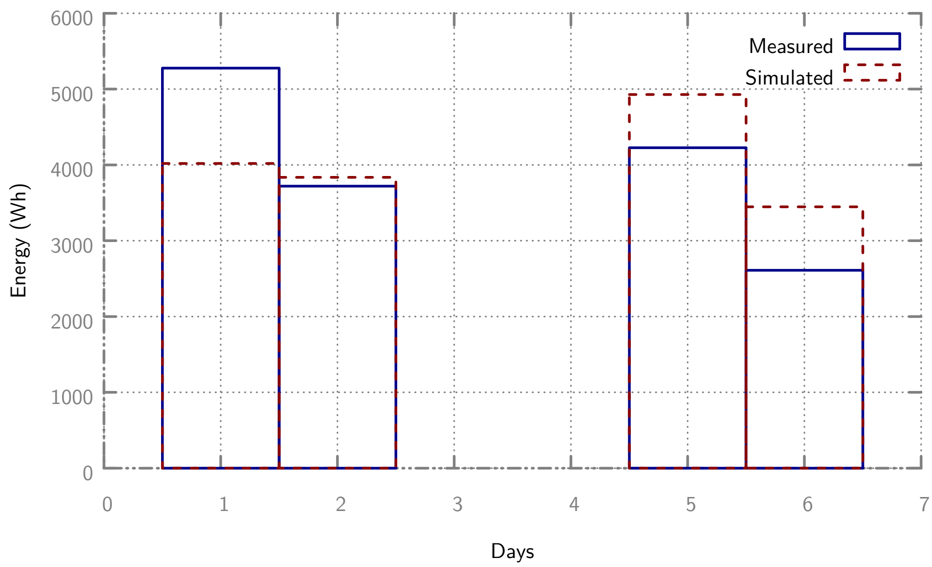

Figure 6.18: Heat Energy (Daily): March 15th - 20th 2012 : Garage, Setpoint 19.3°C.

With this in mind, simulation assisted control can be retrospectively be evaluated. The 19th March 2012 dataset for the Garage (the fifth day in Figure 6.18) will be used, as it follows a two day period of inactivity during the weekend. This will be covered in the following section.

6.6 Optimum Heat start up

This section describes how the BEMS can benefit from BEPS based predictive control. This will be a retrospective evaluation that looks at a previous dataset and how optimum heat start up is envisaged to work, rather than an evaluation of a real-time implementation, since the simulation model was not finalised during the time of the study, and the final integration described in Chapter 4 did not take place.

During the study, the BEMS automation layer scheduled the heating to activate at 6am. In the Garage, setpoint would often be reached well before the time the house was occupied (the latter was around 9am), wasting potentially over an hour of heating in a house with no occupation.

Optimum heat start up is a control strategy that is used to predict the ideal start up time to activate the heating to reach a setpoint at a desired time. In this way, energy is saved, and the delayed start can make use of forecasted ambient temperature increases.

The traditional optimum heat start up controller in current BEMS only learns how quickly the building reaches the desired temperature and brings the heating on at just the right time to achieve the correct temperature as people arrive. However, this type of optimum start controller cannot anticipate forecasted extremes (e.g.excessive solar gains), having to relearn the experience.

If we recall, a simulation assisted controller can operate beyond the range of learned experience to anticipate these forecasted extremes, by simulating the thermodynamic physical processes occurring in and outside the building, making it a desirable feature to have in the control core of a BEMS.

In the results previously presented for calibration and validation, ESP-r's basic heating controller was used, which closely represented the BEMS simple on/off heating, and similarly employed the scheduled method of operation to simulate BEMS automation. It has been shown that there is good agreement between the BEMS and BEPS response, and they appear well synchronised in terms of automation. Since this is the case, we can now further explore how to optimise scheduling by implementing predictive control.

ESP-r does have an implementation of an optimum heat start up controller, based on the BRESTART self-adaptive optimum start algorithm by Birtles and John [Birtles *et al.* (1985)], though the software has a couple of caveats under the associated help section [1]. The original algorithm's equation can be used to compute the start up time necessary to reach desired setpoint at a specified time:

$$ln(DT) = A_0(T_p - T_d) + A_1 \tag{6.2}$$

where DT = preheat temperature difference, T_d = desired temperature, T_p = present sensed temperature, A_0 = constant associated with the thermal weight of the building and A_1 = a constant associated with the time between switching on the heating and the interior starting to heat up

The equation was later modified to include an outside air term, to take into account low outside temperatures :

$$ln(DT) = A_0(T_p - T_d) + A_1 + A_2 T_a o \tag{6.3}$$

where A_1 = a constant associated with the outside air temperature, $T_a o$.

[1] "pay attention to the predicted performance", and "some graphs in the results module might not plot correctly. Use this control with care."

6.6.1 ESP-r's built in implementation

ESP-r's optimum heat start up controller function has additional supplementary inputs compared to the basic on/off controller for desired setpoint, time of arrival and default start time. These were input as 21°C, 9am and 4am respectively. ESP-r would unfortunately provide undefined results for all zones when attempting to use this function (outputting only NaNs[2], suggesting errors in the simulation calculation). This specific controller has been rarely used or tested (according to the documentation). Instead of finding a solution to resolve any issues within ESP-r (which could take months of debugging), it was decided that a higher level solution external to ESP-r would be devised.

6.7 High-Level Implementation of Optimum Heat Start up

The high level implementation for the controller was designed to be scripted externally from ESP-r, using similar techniques developed for automated calibration to find the optimum start up time for the setpoint to be reached by 9am on the 19th March 2012, which was a Monday, following a weekend of no heating activity. A dataset was created in six minute intervals, to permit a wider range of start up times, from the 17th - 19th March 2012. The 17th and 18th March days are included to allow the simulator to equalise to the monitored period. Perl scripts were written to iterate through six minute *start up times*, beginning with a 6am initial start (since this was the original

[2]In computing terms a NaN is Not A Number, a numeric data type value representing an undefined or unreproducible value

schedule), and adapt the BEPS control file with a new heating start time for the Garage zone. Python was used to search and find the index of when the setpoint had first reached 19.3°C for each iteration, by processing the simulation output. The iterations end when the temperature first reaches 19.3°C at 9am.

6.7.1 Results of retrospective evaluated Simulation Assisted Control

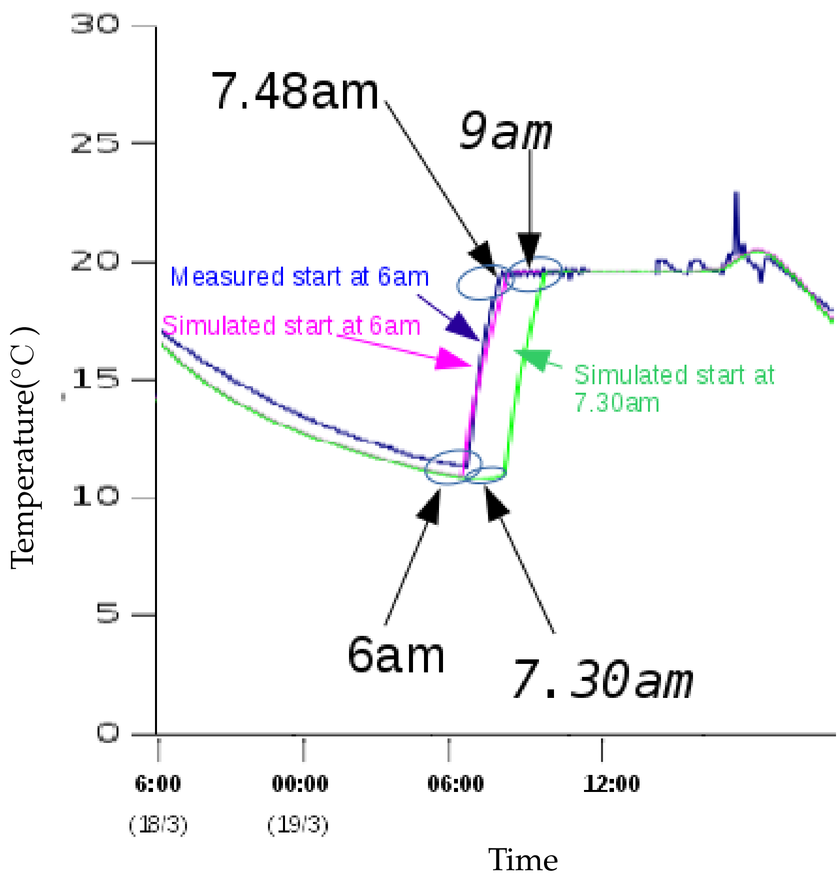

Figure 6.19: 19th March. Scheduled Heating showing that setpoint is reached at 7:48am, and optimum start up should be 7.30am to reach setpoint by 9am

Figure 6.19 graphically shows the results of scheduled and simulated start for Monday 19th March 2012. The blue line represents the measured response, and since a higher resolution data set is used (6 minute intervals, compared to one hour intervals used previously), some additional artefacts can be seen, particularly the spikes towards the end of the curve, representing some minor overheating occurring in the maintenance of the setpoint by the BEMS. This spike is also represented by the simulator, and appears to be due to an increase in external temperature as shown in Figure A.1 (Appendix A).

The measured downward curve shown in Figure 6.19, starting from 6pm on the 18th March is fairly well represented by the simulator response, and the measured and simulated start at 6am on the 19th March is in near perfect agreement, showing that the BEPS is representing the BEMS heating control system effectively, as shown by the purple simulated gradient tightly aligned with the measured data. These two features demonstrate that the simulator is responding well enough for this evaluation and highlights the problem with scheduled heating starting at 6am, in that the setpoint is reached at 7:48am, leaving over an hour of wasted energy in maintaining a setpoint with an arrival time of 9:00am. The results of the optimum start search have predicted the start up time should be at 7.30am rather than the scheduled time at 6am. This is represented by the green line in the figure, and demonstrates the effectiveness of employing predictive control using BEPS tools, and is an example of how simulation assisted control can enhance the control core of the BEMS to save energy - in this case by delaying the switch on time for the heating system as part of an optimum heat start up control strategy.

6.8 Summary

This chapter has built upon the information provided from previous chapters and mainly covered the validation of the building model presented in Chapter

4 to determine its usefulness for simulation assisted control. Overall, it can be said that BEPS models, when supplemented with a full set of building information (e.g. from a BIM) and climate data, can be used for predictive control. Furthermore it has been demonstrated that calibration should be used sparingly and building information should always be sought to adequately represent the building dynamics. In other words, uncertainty should be minimised with actual building data, as much as possible, since the complexity of physical interactions and multitude of building parameters can yield different models, especially when using widely adopted goodness of fit metrics such as those specified by ASHRAE.

BEPS has great potential to improve control in BEMS and further explorations into other control strategies should be encouraged for other applications. The ability to forecast building behaviour with a BEPS integrated BEMS can undoubtedly save energy in homes and other buildings. To further illustrate this, recalling Figure 6.5, which shows the Temperature response for the Garage in March, if the heating was desired at a specific time on the third day, the BEPS could predict (with forecast climate data and a lookahead of several hours) that in fact the space would be passively heated and heating would not be required.

Looking at the bigger picture, as BIMs become more adopted, they could be readily used in BEPS integrated BEMS solutions to forecast building dynamics and behaviour, and open new ways to automate building services. One interesting outcome of this study has been the ability to accurately predict solar gain behaviour (with the only caveat being the solar sensor is adequately calibrated at least once a month to reflect the changes in solar angle throughout the year).

This can be of great benefit for passive solar heating applications that require an element of building control to actuate devices to increase solar energy collection and storage. In such an application, the ability to accurately forecast solar climate data, coupled with pre-emptive building automation, can also potentially lead to new passive solar designs.

To conclude, harmony between BIM, BEMS and BEPS is highly encouraged and should therefore be further explored, to enable better ways to design buildings and their energy management systems.

Chapter 7

Conclusion and Future Work

This thesis has focused on the concept of predictive control in BEMS using building simulation models. The core focus considers the fact that BIMs can present a solution for providing building specific information to create models that can be used in BEPS, as opposed to developing models using inverse data driven techniques. Aside from the key benefit of being able to use pre-existing models for predictive control, and not having to extensively develop one from inverse data driven modelling approaches, BEPS models also consider airflow and thermal domains using validated solvers, whereas black box or grey box models often tend to narrow their focus down to only consider the thermal domain, which require further validation with measured data. This enables a more in depth and complex approach to analyse building energy dynamics, where potentially more accurate predictions can be generated and when supplemented with a full range of forecasting data (external temperature, solar radiation and wind).

Though a model has not been created from a BIM, the information used to create it has been equivalent. This has been ensured by using the same source data that would be otherwise be used to make one. Further consideration has also been given with regards to dividing the model into zones, which are the fundamental units of thermal and airflow domain calculation used by BEPS during simulation. Though current BIMs can contain information useful to BEPS (i.e. geometry, materials, operations, site location), the definition of zones in a BEPS model requires additional modelling detail, not found in BIMs.

At the moment BIM - BEPS translation is a semi-automated process, and with the architectural industry's gradual adoption of BIM to manage workflow, energy analysis is also being carried out using BEPS tools early in the design process, to simulate and optimise buildings. What is currently lacking is further integration of the BEPS enabled BIMs to be used in BEMS, and this is what this thesis has addressed. Though this gap is being lessened, with BIM being used as a monitoring aid in BEMS, particularly for lifecycle and facilities management - as proven by this thesis, there is tremendous benefit to utilise a BEPS enabled BEMS for predictive control.

This has been demonstrated in this thesis by:

- Creating a BEMS platform for a building
- Developing a BEPS model of the building
- Validating the BEPS model with BEMS data
- Retrospective evaluation of simulation assisted control, by comparing BEMS operational data with BEPS simulated operational data

The importance of having a fully populated BIM for BEPS has been shown by introducing uncertainty in the model, and the difficulties have been highlighted when determining uncertain parameters through calibration.

Calibration involves iteratively modifying the BEPS parameters, until there is a high goodness of fit between the simulated and measured data. Goodness of fit criteria were defined for both temperature and energy response loads based on current ASHRAE guidelines for hourly simulations, which employs the CV(RMSE) metric in the statistical comparison of measured and simulated data and deems a model to be have a low level of uncertainty when this value is under 30%. Though this could be achieved for temperature comparisons (with the lowest zone level comparison computed to be 5.85% during validation), when comparing hourly zone heating loads however, the CV(RMSE) was consistently above 100%.This is due to the CV(RMSE) metric punishing large deviations between hourly energy comparisons for measured and simulated data. This metric was originally proposed to evaluate goodness of fit between whole building monthly electricity consumption (which itself could be composed of simpler loads which can be easier to quantify, such as casual gains from lighting, appliance use, etc), and when used to compare energy loads, especially, electrical heating loads at the zone level, it provides no useful assessment due to the high variability in consumption, from hour to hour. A better approach has been found to graphically analyse the heat load to determine if there is goodness of fit, though a new metric should be devised, to consider variations in energy delivery per zone, when using a electrical method of heat delivery.

Furthermore some characteristics of the heaters used have not been able to be fully realised. In particular the use of a far infrared heater in the Master Bedroom, which predominantly uses a radiant method of heating is not an available plant component within ESP-r, and in a separate study had to be a modelled as zone. The model has also assumed 100% heat energy injection at surfaces (equivalent to where the heaters were located in the house), whereas in reality, even though electrical methods of heating are very efficient, there will be some unaccounted losses due to internal control systems actuating the system differently to the simulator's control system (timing differences), or even oil properties of oil-filled radiators, such as the specific heat, which will also affect the overall energy response at a granular level.

Aside from this issue, the temperature response of the model has been very accurate, and the model itself required one minor calibration to determine the density of glasswool in the external wall of the house. The house has been modelled with significant detail and further considers the subtle differences in external wall constructions, where some façades have variable finishes or no insulation. This additional accuracy has produced a model that has high goodness of fit when comparing the measured indoor temperature BEMS data with simulated data during validation. It can be therefore said, that detailed information should always be sought when creating a building simulation model, and calibration should only be used as a last resort.

This thesis is also one of the few studies that has looked solar gains in a residential house, and the effect it has on indoor temperatures, notably when having the ability to forecast solar radiation. Having a BEPS enabled BEMS can aid the control core in deciding whether heat needs to be delivered to space, especially when the space has been predicted to be passively heated through solar gains. This is not only useful for heating, but conversely can also be used in cooling prediction applications, to forecast the optimum *cool* start of air conditioning units for hot and tropical climates. However it has been shown that having accurate solar measurements is required, due to the sensitivity that solar gains can have on spaces with large south facing openings. In particular, this means that solar forecast data also needs to be accurate to carry out useful predictions. Solar radiation forecast data at the moment is costly to acquire, since it uses highly specialised models such as SolarGIS. [1]

7.1 Future Work

This study has resulted in the creation of a SAC enabled BEMS platform and a demonstration of the savings that could be made by integrating a building model with a building energy management system for predictive control. Further development is highly recommended to continue this work, in particular to test and evaluate a real-time implementation.

7.1.1 Real-Time Simulation Assisted Control Evaluation

Simulation assisted control in this study was evaluated retrospectively. In a future study, the platform could be used to attempt real time simulation assisted control using forecasted weather data, and tested over longer periods of time to assess fluctuations for various different climate profiles. This would also require a decision making tool, or ranking system to assess which would be the best simulation outcome, based on additional factors, such as being able to predict occupancy profiles accurately.

7.1.2 Model Variations

The building model for SAC can be varied in a number of ways, depending on the end use application. These shall be discussed.

[1] SolarGIS - http://solargis.info/

7.1.2.1 Cooling environment

This thesis has focused on prediction of heating system use. The same principle can however be applied to a cooling system such as an air conditioning unit, whereby an optimum cool start time can be determined. It is expected that solar gains in such an application will be a dominant consideration, and the modelling of shading and actuation of blinds will feature heavily as part of the control core. ESP-r can also be used with lighting simulation tools such as Radiance, to determine control points based on a sky model and internal illuminance sensing [Fontoynont (2014)].

7.1.2.2 Boiler and Wet Central Heating System

This thesis has considered an electrical heating system, using basic on/off control. A more complex system of modelling a boiler and simulating a wet central heating system, with zoned thermostatic radiator valve (TRV) control can be developed for a SAC application. Alternatively an underfloor heating system can be modelled, whereby the floors are heat generating surfaces. TRVs can now be controlled wirelessly, and are available as Z-Wave enabled devices, which can be integrated into the prototype BEMS developed in this thesis.

7.1.3 Platform Development

With this platform developed, there is plenty of scope to carry out future work. The complete platform (including building simulator), was prototyped to run exclusively on embedded Plug computers. At the time, the Plug computer used (Sheevaplug) was state of the art. Now cheaper alternatives such as the Raspberry Pi could be used, to act as the simulation assisted building controller. ESP-r was compiled successfully on the ARM based Sheevaplug, and it could be possible that a Raspberry Pi build may also work, since it is also based on similar ARM architecture. The low cost of the Raspberry Pi is attractive, has a well supported development community, and is the basis of several automation projects, with some leading to commercial products. Therefore, the system created for this study presents itself as a potential product opportunity, which can be rapidly prototyped with low cost computing solutions such as the Raspberry Pi. An example of such a product could be a SAC enhanced smart thermostat, akin to the Nest Learning Thermostat or British Gas Hive, but with the ability to predict using the architecture presented in this thesis.

7.1.4 Automation in BEMS, Sensor Placement and Simulation Development from BIM

There is potential to automate the full configuration of a BEMS from a BIM. In this way, a BEMS design could be generated with a simulation model, making best use of an optimum sensor placement to provide accurate building model calibration. For instance, a simulator loaded with a daylighting model would ensure temperature sensors were not placed in direct sunlight, and at the same time ensure, daylight sensors were aligned in the optimum locations. This would require a significant amount of work in the area of building data translation, but a successful implementation would have a great impact in the building and construction industry.

Appendix A

Climate Data : March 15th - 20th 2012

A.1 Temperature : BEMS

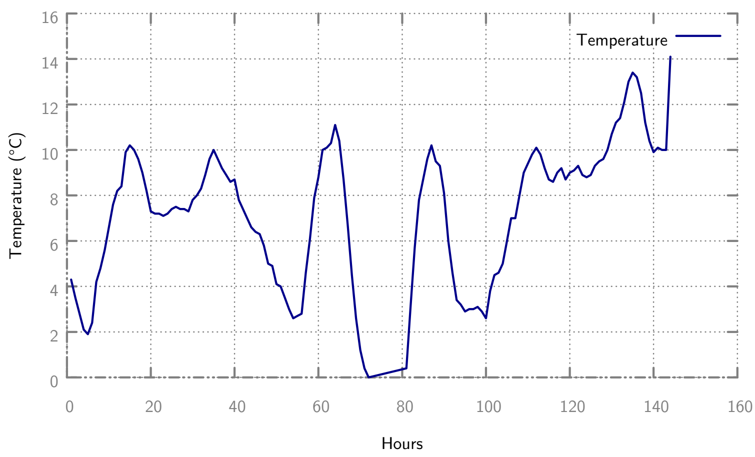

Figure A.1: External Temperature from BEMS : March 15th - 20th 2012

A.2 Humidity : BEMS

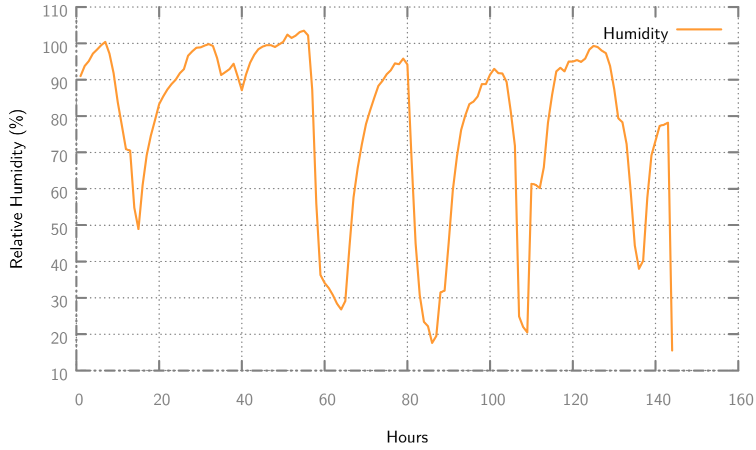

Figure A.2: External Humidity from BEMS : March 15th - 20th 2012

A.3 Solar Radiation: BEMS

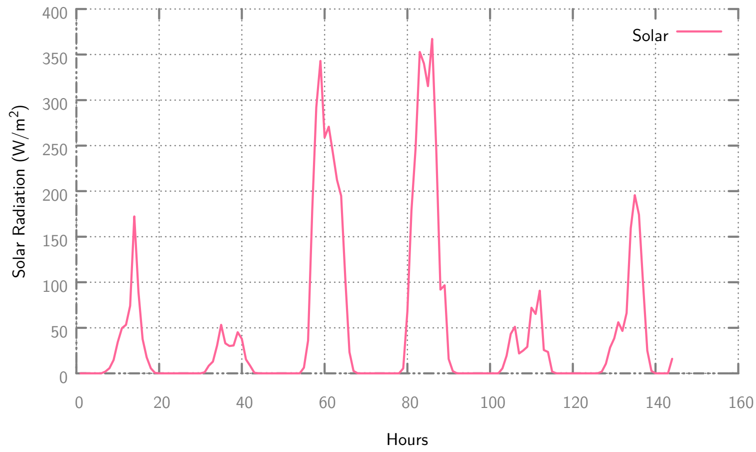

Figure A.3: External Solar Radiation from BEMS : March 15th - 20th 2012

A.4 Wind Speed: Weather Underground (Wishaw)

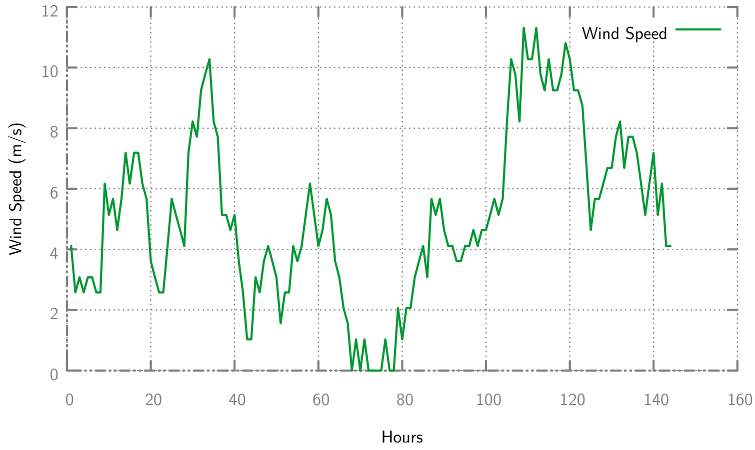

Figure A.4: Wind Speed from Weather Underground : March 15th - 20th 2012

A.5 Wind Direction: Weather Underground (Wishaw)

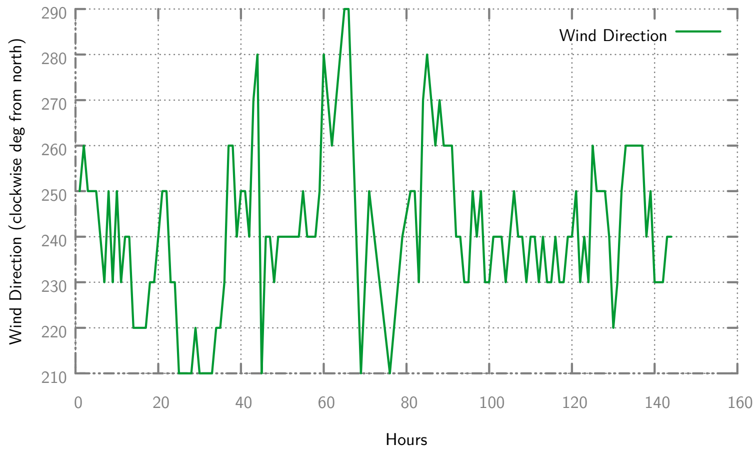

Figure A.5: Wind Direction from Weather Underground : March 15th - 20th 2012

Appendix B

Climate Data : September 10th - 17th 2012

B.1 Temperature : BEMS

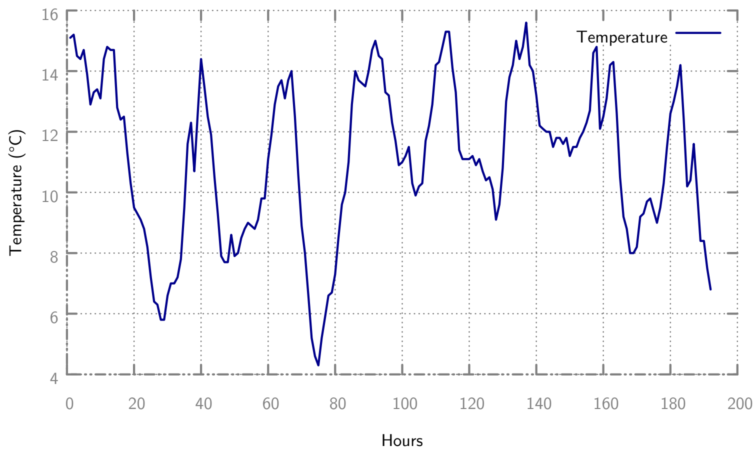

Figure B.1: External Temperature from BEMS : September 10th - 17th 2012

B.2 Humidity : BEMS

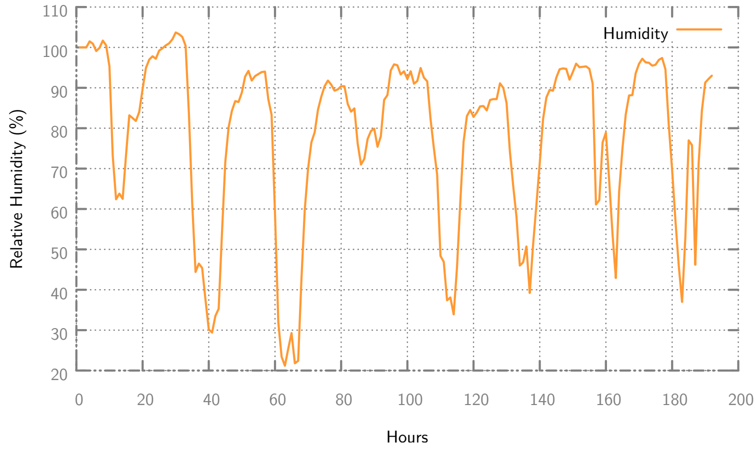

Figure B.2: External Humidity from BEMS : September 10th - 17th 2012

B.3 Solar Radiation: BEMS

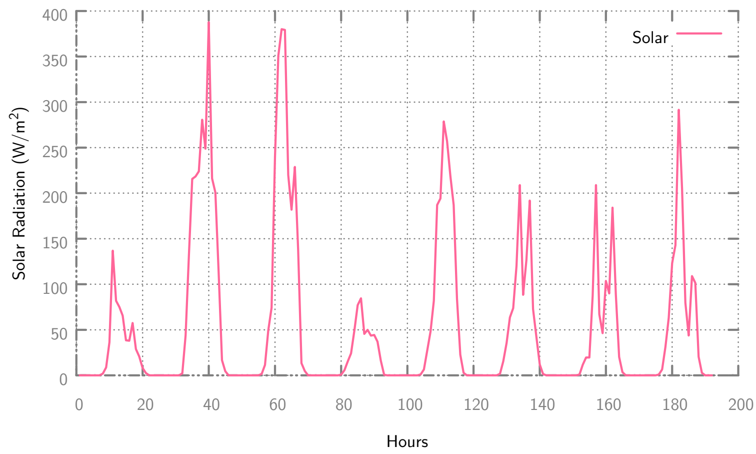

Figure B.3: External Solar Radiation from BEMS : September 10th - 17th 2012

B.4 Wind Speed: Weather Underground (Wishaw)

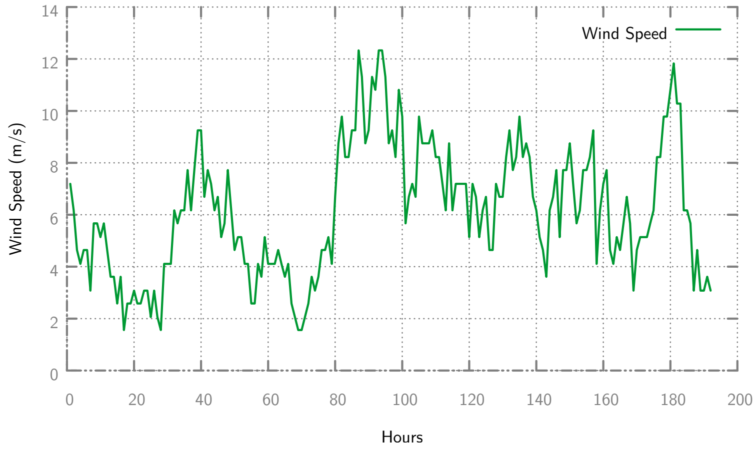

Figure B.4: Wind Speed from Weather Underground : September 10th - 17th 2012

B.5 Wind Direction: Weather Underground (Wishaw)

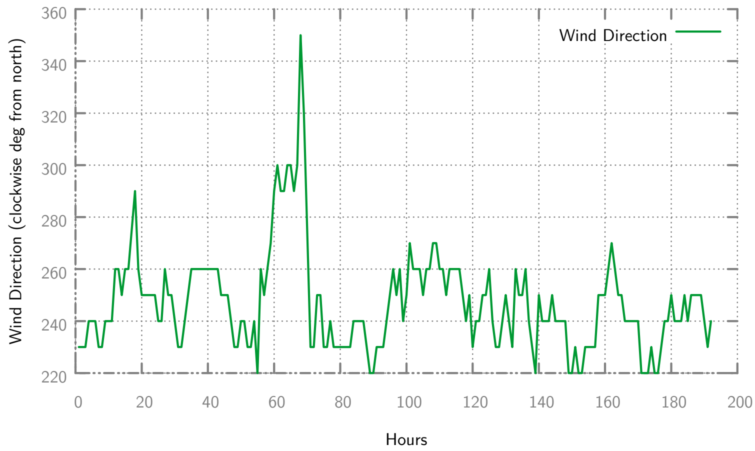

Figure B.5: Wind Direction from Weather Underground : September 10th - 17th 2012

Appendix C

Original Publications

Seeam, A., Zheng, T., Laurenson, D., Lu, Y. and Usmani, A. (2013a). Structural Health Monitoring And Simulation Assisted Building Management Systems For Modular Buildings. *In The 6th International Conference on Structural Health Monitoring of Intelligent Infrastructure*.

Seeam, A., Zheng, T., Lu, Y., Usmani, A. and Laurenson, D. (2013b). BIM Integrated Workflow Management and Monitoring System for Modular Buildings. *International Journal of 3-D Information Modeling, 2, 1728*.

Seeam, A., Zheng, T., Lu, Y., Usmani, A. and Laurenson, D. (2011) . An Integrated Monitoring System For Modular Buildings. *In The 5th International Conference on Structural Health Monitoring of Intelligent Infrastructure*.

STRUCTURAL HEALTH MONITORING AND SIMULATION ASSISTED BUILDING MANAGEMENT SYSTEMS FOR MODULAR BUILDINGS

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ABSTRACT

As part of a Knowledge Transfer Scheme in the UK, the authors worked closely with a manufacturer of modular buildings using a volumetric construction process (custom built steel frame modular units which are then transported for rapid erection onsite). The manufacturer was looking to improve their processes and develop intelligent buildings, by integrating a wide range of sensors and control systems for optimising energy efficiency and monitoring structural health, particularly in earthquake regions. A suitable scheme was devised that would take advantage of the modular method of construction in terms of design, installation, and monitoring of modules. A bespoke integrated system, performing both building management functions and structural health monitoring (SHM) was designed, developed and installed for a modular sample house. The building management system comprised a wired bus network of sensors (1-Wire) and wireless control of heating and lighting using Z-Wave technology on a low power ARM platform, containing a comprehensive monitoring database. A TCP/IP based SHM System was integrated directly into the platform, acting on the same database, using Power over Ethernet networked Arduino micro-controllers which directly monitor displacement and vibration and assess structural health. A 1-Wire strain gauge was specially developed to integrate and share the existing 1-Wire bus network of the building management system, allowing daisy-chaining of resistive foil strain gauges, simplifying cable deployment of SHM in module installation. The further integration of a dynamic building simulation tool, ESP-r, was also explored by exposing a simulation model with monitored data from the management system to develop simulation assisted control strategies which could optimise heating control.
The full paper will be presented as a case study, describing detailed aspects of the integrated system and discuss a selection of results from the data collected by the monitoring system and implementation of the simulation system.

KEYWORDS

BIM, modular structure, volumetric construction, prefabrication, building management, structural health, simulation

INTRODUCTION

The KTP scheme in the UK is used to drive forward company innovation by collaborating with university departments. KTP Associates are appointed to work closely with the company under direction of the academic partner. In this case, two KTP Associates, early career researchers, were appointed for their complementary and broad range of skill-sets ranging from structural engineering to systems engineering. The interdisciplinary nature of the project was reinforced by support from a dedicated team of high-calibre academics in the Institute of Infrastructure and Environment and the Institute for Digital Communications at The University of Edinburgh. The KTP scheme is funded by the Technology Strategy Board. The company partner, Enemetric who benefited from this partnership, are an innovative modular construction company, based in Scotland, who were looking to diversify and create competitive advantages in a construction industry looking for higher efficiencies, in challenging times post-recession. Enemetric are driven to make their buildings intelligent, by integrating optimised sensors and systems early in the construction process. By instrumenting the building early with sensors, the building will be able to self-monitor itself, and optimise control systems, while also monitor structural health, throughout the construction process, beginning with off-site fabrication and ending with building erection. For instance, the modules' structural integrity can be monitored and logged via factory instrumented sensors, during transportation and assembly. The motivation behind these developments was driven by the need to create an integrated system, which aligned with their ethos of rapid construction, efficiency and less waste, compared to traditional building manufacture. This paper is divided into two main sections. The first describes the Building Management System and its various layers of operation, and the second discusses the design of the Structural Health Monitoring System, and its integration

BUILDING MANAGEMENT SYSTEM FOR MODULAR BUILDINGS

Designing a Building Management System (BMS) that can be integrated into the structure of modular buildings requires an additional level of planning. The authors discussed the use of Building Information Modeling (BIM) for modular buildings in a previous paper, Seeam *et al.* (2013), noting the benefits data reuse brings, in terms of planning (e.g. project scheduling, enterprise resource planning) and workflow (data sharing amongst groups), and methods with which the data can be managed and exploited for various uses beyond the standard BIM definitions (e.g. manufacture). When data is created to design the building (e.g. initial CAD models), the same information (i.e. raw building data such as geometric dimensions, material properties) can be used in a different building design or engineering application (structural design, energy modeling, and manufacturing). In the case of BMS design and installation, the BIM can be used to inform the number of sensors required in advance, the control points and also aid the design of cabling infrastructure. This can only be achieved by virtually representing the building as a BIM to understand building performance (e.g. with dynamic building simulation tools), and therefore what needs to be monitored and controlled for optimal operation. In this way sensor information can augment the BIM, Ozturk *et al.* (2012).

Design

Enemetric's method of construction translates well into the BIM methodology in terms of object oriented design, and can also be viewed from structural and energy perspectives, which in turn can help to understand some of the BMS requirements, particularly with respect to sensor requirements. A whole building object is composed of many module objects and each module has a structural relationship with adjacent modules. Each module is made up of beam objects, with internal steel framing objects, with load requirements. Structural sensors (e.g. strain gauges) can be informed from the module load relationships in the building information model. The structural representation (view) of the BIM highlights the optimal areas of the building for efficient and accurate structural health measurement, and the number of and types of sensors required (accelerometers, displacement sensors,etc), depending on the geographic location, and ground foundation of the building. Rooms can be considered objects, as are windows, doors, floors, etc. In terms of energy balances, rooms will have relationships with other rooms, with respect to heat transfer. Temperature sensors and accurate placement can be informed from the building information model. For instance, supplying a building simulation model, with solar data, can aid optimum sensor placement, to avoid areas where solar gain may have an effect on sensor readings. Each room itself will contain objects for lighting, heating, etc. There will be sensor and actuator objects and relationships. One sensor object may be related to several actuators (Motion sensor for light control, or intruder alarm).

Installation

When considering to implement a BMS for a Modular Building, certain design implications come into play which differentiates it from a traditional building. In a traditional building, BMS installation comes much later in the construction process, at a stage when most of the building has been completed. In some cases the BMS is often an afterthought, and installed with little consideration of the building form. One then needs to consider installation procedures at the factory stage when the building has been decomposed into modules in the off-site factory. Using BIM, the design of the topology of sensor infrastructure can be considered as an additional group of building management layers, taking into account the design discussed earlier, in terms of module relationships. In the case of Enemetric and building installation, their modular system is based on a unique connector system which connects volumetric modules into place. This connector system and their construction methods have been described in Seeam *et al.* (2011). Furthermore to being structurally connected, services (plumbing, electrical) are similarly connected between modules greatly simplifying installation when it comes to building erection. This particular feature allows for an additional BMS service (i.e. sensing infrastructure) to be added to the existing building services layer, by running an additional cable alongside. After a thorough investigation into the suitable building automation protocols for a wired sensing infrastructure to satisfy the service requirements, it was decided that the 1-Wire system would align well into this concept. 1-Wire is a simple but robust protocol that has features such as 64-bit unique factory burned addresses and the ability to transfer data and power over notably long distances (300 metres with repeaters). One 1-Wire node acts as a master controller and all other nodes are slaves, which can operate in bus, star or tree topologies. In terms of accurate sensing, wired technologies will provide a faster response, compared to wireless technologies. Fast sensor response is required for an efficient control system, which can quickly react to changes in the environment. Furthermore, structural health can be monitored in real-time. Looking at the design of an Enemetric Modular Building, and comparing the whole building to a tree, with modules as branches, and leaves as sensing nodes, 1-Wire complements this analogy well, and is suited to this type of networking topology (Figure 1). 1-Wire essentially operates as a bus topology (main trunk), which can branch out (modules) into a tree topology with leaves (sensors).

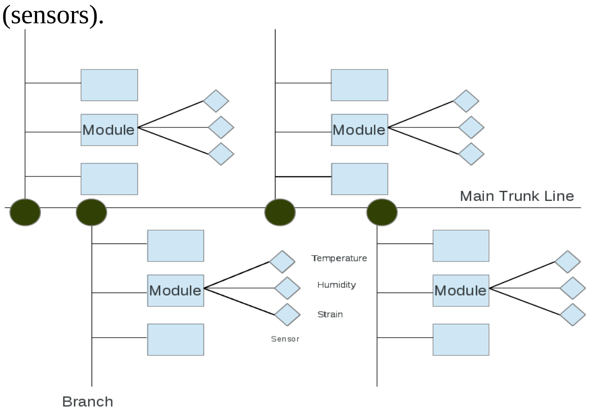


Figure 1. Sensing infrastructure topology applied to modular building

In small buildings (such as a house used in this study), an implementation like this would be suitable, but for larger buildings, a more complex topology would be needed to support redundancy using several 1-Wire master controllers. 1-Wire was used to create a new design of strain gauge for the Structural Health Monitoring system, by interfacing an op-amp conditioned Wheatstone Bridge with a 1-Wire DS2450 Analog to Digital (A/D) conversion chip. Wireless protocols require a less documented method of installation, but installation still needs to take into account certain characteristics of wireless mesh networks, such as distance limitations between nodes and the frequency used for communications. Z-Wave was chosen as the wireless protocol for a smart home implementation. Though limited to 232 nodes, Z-Wave operates in the sub-GHz range, so does not compete in busy 2.4GHz spectrums shared by WiFi (IEEE 802.11) and Bluetooth (IEEE 802.15.1). This is the case with Zigbee (IEEE 802.15.4), which is a prominent technology in the building automation space. Furthermore, Z-Wave is a truly interoperable protocol, with devices from many manufacturers being able to talk and communicate, over a standard messaging structure. Zigbee, on the other hand, though an open standard, has messaging profiles, which can be adapted by the device manufacturer, leading to one box solutions, where one manufacturer's sensor cannot talk to another. In contrast, the Z-Wave Alliance requires a license fee for device implementation, but all Z-Wave devices can communicate with each other.

Sample House Implementation of BMS

An embedded plug computer (SheevaPlug) was used as the BMS controller, and bespoke software was developed around the Linux Operating System (Debian), using the perl programming language to monitor, control, automate and process climate files for the simulation layer. A BMS perl library was built to satisfy the layer interaction requirements and interface between the various parts of the system.
The various layers to the system are as follows.

1. A monitoring layer which records sensor values from the environment and structural health.
2. A control layer which provides interfaces to allow user interaction with actuators.
3. An automation layer which acts upon various user rules set in the system against monitored values using the control layer (e.g. heating setpoints).
4. A simulation layer which used the values from the monitored layer to forward predict automation strategies.

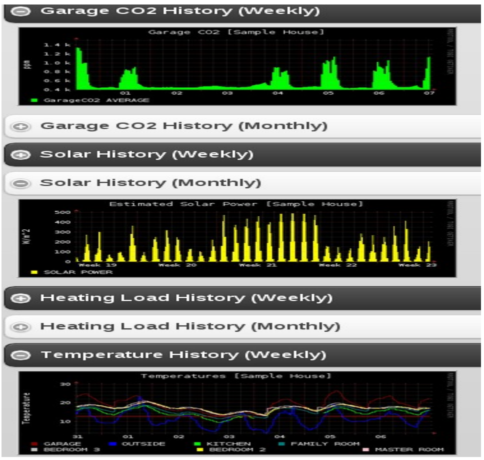
Monitoring Layer

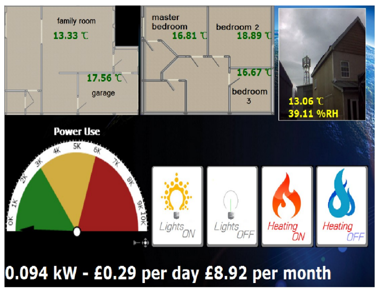
The Monitoring layer was composed of three monitoring sub-layers, one for the environment, one for structural health and for energy (in this case only electricity). The structural health monitoring system is discussed in greater detail in another section. The environment monitoring layer was built upon a 1-Wire network of sensors which monitored temperature, humidity, light levels and carbon dioxide. The 1-Wire sensors were exposed as a unix file-system using OWFS software (i.e. mounted as files which can be read using unix commands such as 'cat') communicating to a 1-Wire master controller (LinkUSB) which interfaced to the SheevaPlug's USB interface. Data from these sensors (Table 1) were measured once a minute and stored in a time-series RRDtool Database. Compared to SQL based databases, RRDtool databases are created with a fixed size, and older values are discarded as new values enter beyond the archive limit set. Thus, this implementation is ideal for embedded applications. RRDtool also has built in support for graphing facilities (Figure 2b). The 1-Wire system reacted quickly to changes in sensor values, and the one minute interval was suitable for the control layer, to turn on and off actuators in a timely manner

Table 1. Sensors used in the 1-Wire Network

Measurement	Sensor	Unit
Temperature	Maxim DS1820	Celsius
Humidity	Honeywell HIH-4031-001	Relative Humidity
Light Level	Clairex CLD240	Lux
Carbon Dioxide	SenseAir K30	Parts per million

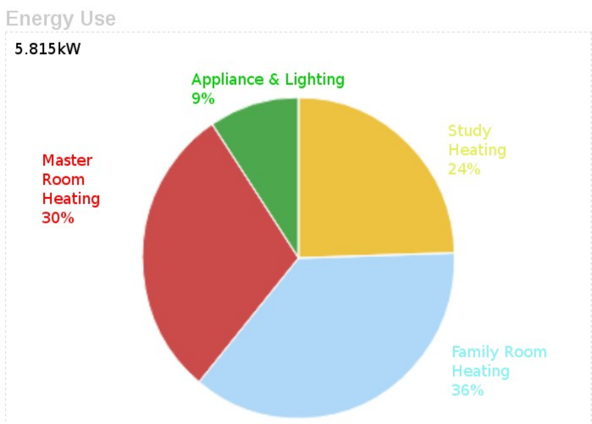
For the sample house, measurements for temperature (Figure 2a) were taken in all living areas (bedroom, living room, etc.), and a humidity measurement for both the first and ground floor. Carbon Dioxide was measured in the Garage which was used as an office space, and occupied every day by the KTP Associates to work and research. This measurement can be used as an indicator of air quality, and to a certain degree, occupancy. Light level measurement was only monitored externally, along with external temperature and humidity from sensors housed in a purpose built wired weather station mounted on the roof of the protruding garage.





(a) Interface showing floorplans and temperatures (b) Interface showing graphical data

Figure 2. Two web interfaces developed showing real-time and historical data



a) Real-time energy disaggregation b) IAM c) Current Cost Display

Figure 3. Current Cost Energy Monitoring

Electricity was provided to the sample house, and distributed through dedicated circuits for lighting and appliances. Gas could not be supplied at the site due to planning restrictions, therefore a wet central heating system (as commonly installed in homes in Scotland), could not be used, and thus electrical oil-filled radiators and fan heaters were provided for testing heating control. A Current Cost Energy Monitoring solution was used to measure the aggregate electricity consumption (Figure 3c) at the meter, and three individual appliance monitors (Current Cost IAMs, Figure 3b) were used to measure the electricity consumption from the radiators to determine the heating load. Simple disaggregation was performed to separate the heating loads from appliances and lighting dynamically, and shown on the control interface (Figure 3a). Data was collected every 6 seconds, summed and averaged over a minute, and stored in the RRDtool database.

Control Layer

The control layer was built around the Z-Wave protocol to actuate heating and lighting. Parts of a Z-Wave perl script[1] were modified and implemented in the BMS perl library. Only the control components of the script were needed and implemented. The Z-Wave actuators used are shown in Table 2. Lights could be directly controlled from a web interface (Figure 4), using on-screen buttons and gestures (swipe up to brighten, down to dim) on a touch screen interface.

Table 2.Z-Wave Wireless Actuators

Actuator	Control
HomePro ZRP210	Heating via Appliance Control
HomePro ZDW232	Lighting

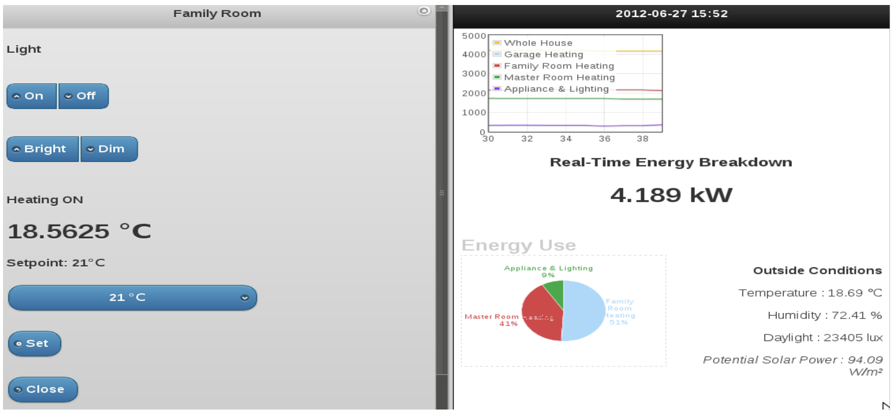


Figure 4. A set of user interface controls were developed and tested over the course of the partnership (These ranged from native Android applications, to X-Windows and HTML5/jQuery touch screen supported web interface shown here)

Automation Layer

The automation layer comprised mainly of setpoint control of heating and a daylight reactive setting for dimming of lights. Setpoint control was based on basic on/off switching of the electric heaters, and set using a drop-down box on the control interface (Figure 4). Temperature sensing was performed by the 1-Wire sensors, the Z-Wave plug-in modules switched the heaters, and the Current Cost IAM energy monitor, measured the heating load. Using the light sensor mounted externally, Z-Wave lights were dimmed according to the amount of daylight (daylight factor calculation).

Simulation Layer

Current methods of intelligent learning in buildings, such as Neural Networks require significant amounts of training and are not useful beyond their range of experience. Building simulation though, is essentially a virtual representation of the building, permitting a more accurate set of prediction outcomes and thus more energy efficient control strategies. Coupled with smart grid technologies, such a system would also be able to perform

1http://www.bigsister.ch/zwave/zwave_s

automated demand response for energy reduction and management. Simulation Assisted Control for BMS has seen applications for optimum heating control, coupling ESP-r with Labview, Clarke *et al.* (2002), cooling using TRNSYS with MATLAB, Pichler *et al.* (2011), and assisted lighting control using RADIANCE with a BACnet system, Mahdavi *et al.* (2009).

With the Simulation Model encapsulated in the BMS, the system could act on prediction data, such as Weather Forecast Models, obtained from internet feeds. Furthermore, a BIM coupled with the BMS, can perform self-monitoring of the environment and energy. In this way, the Simulation layer can identify over time whether the building has also been performing as designed, by comparing simulated energy loads (heating, cooling), with measured loads from the BMS. One particular study by Yin (2010), noted a 3% difference in energy consumption between the BMS and a building simulation model, indicating that the building performed as designed in terms of energy loads.

The dynamic building simulation tool, ESP-r was integrated into the system, by compiling the source code for the ARM target platform of the SheevaPlug. A simulation model of the sample house was created, and scripts were developed to convert the database data into climate files for ESP-r. Figure 5 demonstrates successful integration of the Simulation model in the BMS, by supplying sensor monitored data directly into the ESP-r simulator compiled on the SheevaPlug. The automation layer of the BMS maintained a setpoint of 19°C between 6am and 5pm in the Garage for one week, and the simulation layer was programmed with the same scheduling, and heating capacity (2kW).

An imposed climate data set was generated from the monitoring layer using externally placed sensors from Table 1 (temperature, insolation, humidity). The effects of solar gain raising the temperature beyond setpoint can be seen in both the monitored and simulated data. This was due to a large windowed patio doors providing direct access to the garage area (which was used as an office space).

Good agreement (0.92 correlation) has been achieved between the simulated and monitored results, verifying the use of the simulator for prediction. Having an accurate simulation model is important for anticipating demands and future load requirements for the BMS, particularly under extremities and to perform simulation assisted control strategies. The results also further validate the company's low U-values (0.19) for wall constructions, and that the original BIM data is correct.

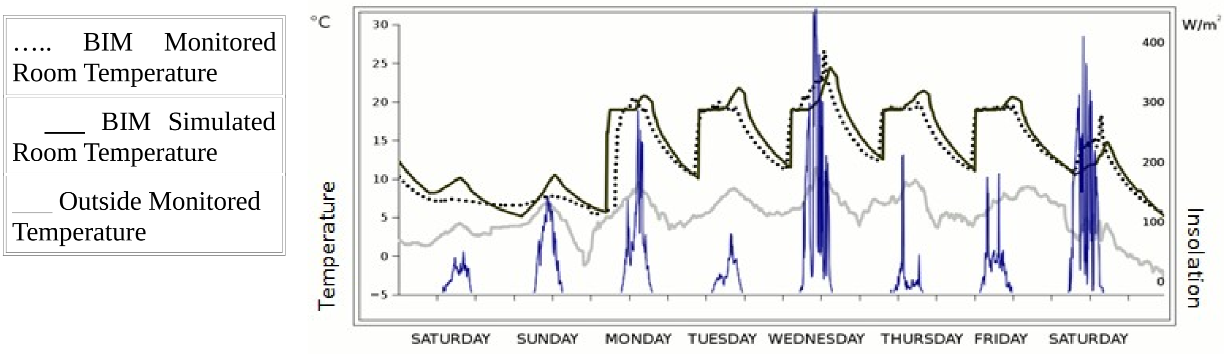


Figure 5. Daily Temperature Response Simulated and Monitored against Solar Processes (W/m^2)

STRUCTURAL HEALTH MONITORING SYSTEM (SHM)

Enemetric Modular Buildings employ a structural system which is highly unconventional, consisting of box shaped modules tied together with post-tensioned steel bars, which are critical to the integrity of the whole structure, especially when it is subjected to lateral loads such as wind and dynamic excitations such as earthquakes.

Although the design has been checked thoroughly using computational models which show that the structural system is safe under these types of loads, the company wanted a monitoring system for the critical elements to provide an additional measure of safety.

The design of the SHM system is based on the failure modes identified from analysing the structural view of the building information model of the modular system, Zheng *et al.* (2012). The SHM system comprises a network of sensors, and the sample house was used as a test-bed to develop the system. Specifically this prototype system was designed with the intention of being further developed for monitoring modular buildings assembled in earthquake regions (e.g. L'Aquila, Italy).

There are 3 distinct components of the SHM system network.

1. A 1-Wire network of strain gauges.
2. An Internet Protocol (IP) network of Arduino based micro-controllers interfaced with MEMs accelerometers and ultrasonic displacement sensors.
3. A Real-time Monitoring interface and Database.

The SHM system was developed with an aim to monitor the "health" of critical elements (e.g. the tying condition and state of connections), as well as the general performance.

1-Wire Strain Gauge

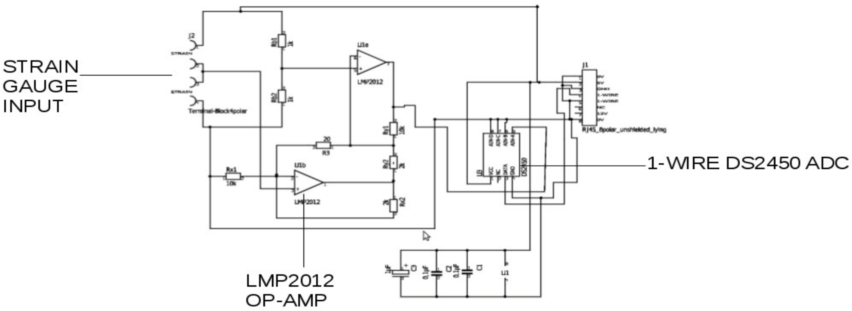


Figure 6. DS2450 1-Wire A/D chip is used in a circuit built to read an op-amp conditioned signal from a Wheatstone bridge

The purpose of the strain measurement is to assess the safety and serviceability of the modules in the building. It was identified that strain can be measured in the primary floor beams, end of posts and corners of the modules, and that most primary beams modules use S275 Steel with a utilization ratio of stress less than 0.6, whereas posts use S355 Steel with utilization ratio close to 1.0. A 1-Wire measurement circuit for strain (Figure 6) was designed to integrate with the BMS 1-Wire network which records data to an RRDtool database.

Strain gauge circuit design

S275 and S355 steel have a Young's modulus of 210GPa therefore strain at the yield point of the steel is 1.31×10^{-3} and 1.65×10^{-3}, respectively. The strain of primary beams is less than 7.86×10^{-4} and that of posts is less than 1.65×10^{-3} in most cases. We chose the smaller value 7.86×10^{-4} as the reference in the structural monitoring system. The resolution of the of the strain measurement should be less than 0.1% of the referred strain, which is 7.86×10^{-7} .With an input voltage of 5.0V, gauge factor of 2.1, and strain resolution is 7.86×10^{-7}, the voltage resolution of the measurement circuit is 2.06×10^{-6}V. The 1-Wire Strain Gauge Circuit measured traditional resistive foil strain-gauges in a quarter bridge wheatstone bridge (Figure 7) with a temperature compensation configuration. The strain is measured from Tokoyo Sokki Kenkyujo Co. Ltd. (FLA-6-11-1L) strain gauges applied to a primary beam with 1m leads 10/0.12 (0.44ohm/m).

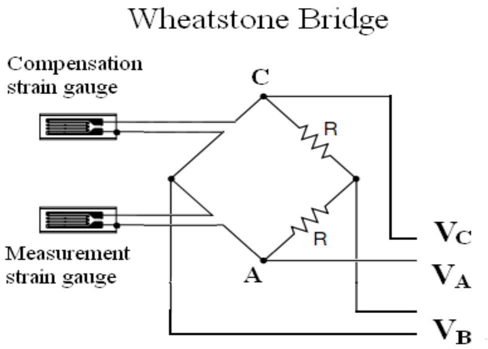


Figure 7. Quarter Bridge Wheatstone used and measurement points

The voltages, V_A, V_B, V_C at junctions A, B and C are measured in the bridge using a DS2450 1-Wire A/D chip and the strain is calculated using:

$$\varepsilon = \frac{1}{K} \frac{4V_B}{A\left(V_C - V_A\right)}$$

Where ***A*** is the Amplification Factor = 1000, ***K*** is the Gauge Factor = 2.1, V_A, Voltage at A, V_B Voltage at B, V_C Voltage at C.

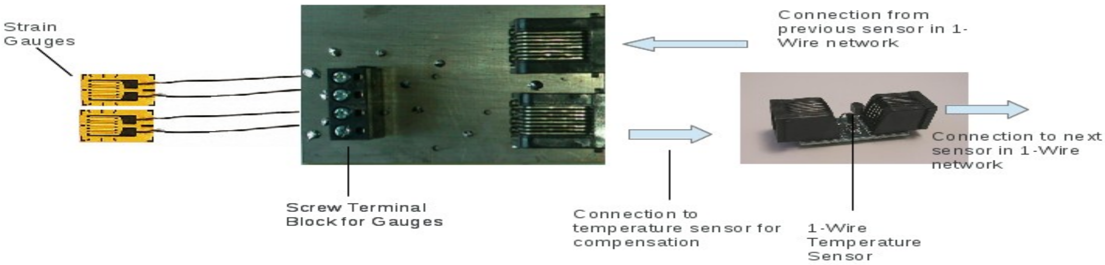


Figure 8. Strain-gauge PCB circuit supporting 1-Wire communication

A PCB with RJ45 connectors (Figure 8) to the 1-Wire network (Figure 2) was built based on the 1-Wire strain-gauge circuit shown in Figure 6. The final iteration of PCB had dual connectors, enabling daisy-chaining of other sensors, such as a 1-Wire temperature sensor (DS1820) for temperature compensation. Maximum strain at the bottom of floor beam is a critical index to the safety of the structure. Once the strain exceeds the yielding point of the material, it indicates that the cross-section has been damaged. The criteria for the strain alarm level have been defined in Table 3. These levels are recorded in the database, according to the strain measurement.

Table 3. Alarm Levels for Strain

Alarm Level	Type	Strain Condition
1	Normal	Strain less than 70%
2	Notable	Strain is between 70% and 100% of the design utilization ratio
3	Serious	Strain exceeds the design utilization ratio but not yielding
4	Damaged	Strain exceeds the yielding point of the steel

Vibration and Displacement Measurement

Arduino micro-controllers were used to perform vibration and displacement measurement. Due to the requirement for high sampling, the 1-Wire network cannot support this type of measurement due to low speed communications, therefore a micro-controller based solution was sought, which would also satisfy the need for having a single wire solution, which in turn, could carry data and power along a dedicated BMS cable in the modules. The Arduinos were programmed as Internet Protocol (IP) clients, communicating to a SheevaPlug acting as a server, and also utilized Power Over Ethernet (PoE), allowing them to be powered over a standard network cable, similarly to the 1-Wire network. As they were developed as IP clients, they also have the ability to be integrated with wireless Arduino shields using IEEE 802.11 (Wi-Fi) protocol, with very little modification, and can be accessed remotely over the Internet.

Vibration measurement and assessment

Vibration measurement is carried out by sampling acceleration measurements from an accelerometer applied to a floor beam (Figure 10a) and computing the vibration frequency from Fast Fourier Transform (FFT), followed by vibration dose calculation suitable for Vibration assessment, determined using criteria set out in BS6472 (Table 4). Notably, the Arduino has been programmed to perform FFT and demonstrate local processing capability, but the full acceleration data is also sent to the SheevaPlug every 2.5 seconds for a further server side FFT calculation using a perl FFT library, which is more accurate and without memory limitations of the Arduino micro-controller. However local calculation lessens the load on the server, allowing more Arduinos to be deployed if the FFT is not performed on the SheevaPlug, which though acting as a server is still an embedded computer, with limited computation power to cope with processing many high frequency sampling sensors over Internet Protocol.

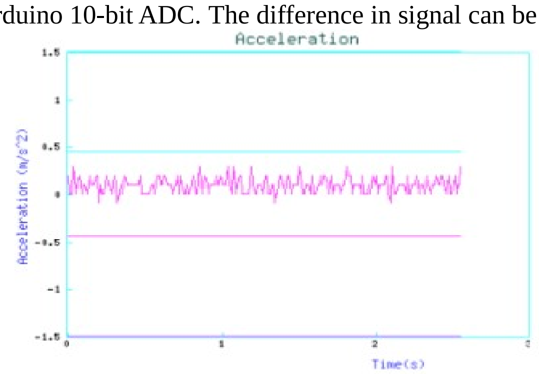
Table 4.Vibration Dose Values ($m/s^{1.75}$) as given by BS 6472-1:2008

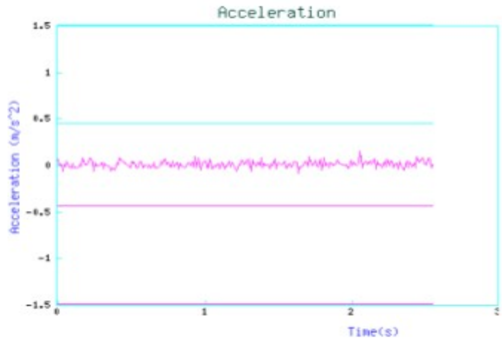
	Probability of Adverse Comment		
Place and Time	Low	Moderate	High
Residential buildings 16h day	0.2 to 0.4	0.1 to 0.8	0.8 to 1.6
Residential buildings 18h night	0.1 to 0.2	0.2 to 0.4	0.4 to 0.8

Table 5. Alarm Levels for Vibration

Alarm Level	Day Dose ($m/s^{1.75}$)	Night Dose ($m/s^{1.75}$)
1	<0.2	<0.13
2	0.2 to 0.4	0.13 to 0.26
3	0.4 to 0.8	0.26 to 0.51
4	0.8 to 1.6	>0.51

The vibration alarm level is specified from the Table 5, and sent to the database to be stored. Two types of accelerometer were trialled. An analog accelerometer (Analog Devices ADXL335), and a digital accelerometer (Bosch BMA180). Analog accelerometers are cheaper, relatively easier to set up but will restricted by the Arduino's on-board 10-bit analog to digital converter (ADC), producing a lower resolution signal, and thus potentially less accurate result. Digital accelerometers are more expensive and have complex set ups requiring an additional layer of communication using protocols such as I2C. This may have an impact on other devices which share the I2C bus and timing. The acceleration measurement however will be determined from the digital accelerometer's own ADC (e.g. 14-bit) giving a signal of higher accuracy than an analog accelerometer with Arduino 10-bit ADC. The difference in signal can be seen in Figures 9a and 9b.



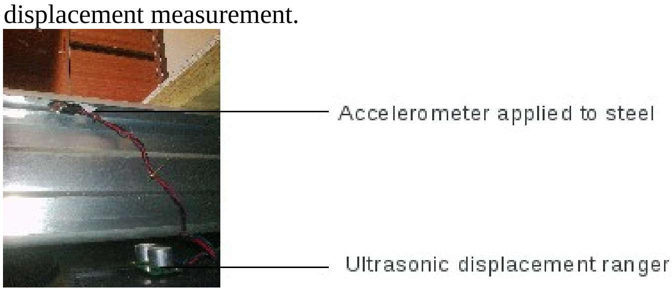


a) ADXL355 with noticeable noise b) BMA180 has a 'smoother' signal

Figure 9. Graph of accelerations from two different types of accelerometer

Displacement measurement and assessment

Displacement measurements are carried out using an ultrasonic distance ranger device (Devantech), and assessments are carried out according to Eurocode BS EN 1993-1-1:2005. The ranger is mounted on the Arduino case underneath the floor (Figure 10b). Maximum Displacement at the bottom of floor beam is a critical index to the serviceability of the structure. Once the Displacement exceeds the maximum displacement required in the design code, the brittle and plaster finishes could be cracked. The criteria for the displacement alarm level have been defined in Table 6. These levels shown in are recorded in the database, according to the displacement measurement.



a) Placement of sensors b) Ultrasonic mounted on Arduino case

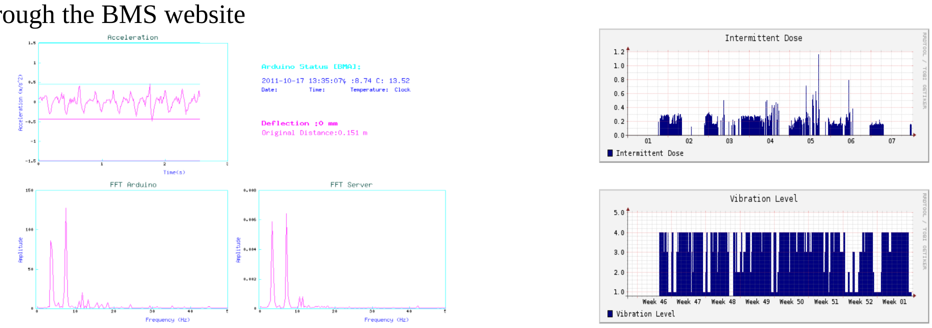
Figure 10. Arduino micro-controllers and their respective sensors

Table 6.Alarm Levels for Displacement

Alarm Level	Type	Maximum Displacement Condition
1	Normal	Displacement is less than 80% of span/360
2	Cracked	Displacement is between 80% and 100% of span/360
3	Brittle	Displacement exceeds span/360 to span/300 as specified in NA to BS EN 1993-1-1:2005
4	Damaged	Displacement exceeds span/300 as specified in NA to BS EN 1993-1-1:2005

Real-Time Monitoring Interface and Database

The architecture of the SHM system utilises the existing BMS SheevaPlug acting as a server networked with two Arduino micro-controllers in the study. The real time clocks of the Arduinos are synchronized periodically with Network Time Protocol (NTP) packets from the server. The Arduino units are self-powered using Power over Ethernet with a TP-LINK TL-SF1008P PoE switch and communicate directly to the server after each instance of local data processing using Hypertext Transfer Protocol (HTTP) over IP every 2.5 seconds. The server then stores the results in the RRDtool database recording vibration level, intermittent dose, dose summation, acceleration, deflection level, strain and deflection. Examples of further server processing includes a real-time view of accelerations (Figure 11a), and time series data of the results (Figure 11b), which can be launched through the BMS website



a) Real-time SHM interface b) Historical data

Figure 11. Web interface views developed for the SHM system

CONCLUSION

This paper has presented an integrated monitoring system for modular buildings, and discussed the layers of operation. The bespoke system, developed as part of the KTP scheme, has given the company a low cost and flexible solution which will enable the company to be more innovative. The concept of SHM being developed as part of our integrated monitoring/control framework has a wider applicability in smart construction and has been designed to be flexible and scalable. Beyond the sample house given to test sensors and research and development, a trial system was installed and successfully tested in a module for a 4 storey flat development.

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BIM Integrated Workflow Management and Monitoring System for Modular Buildings

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ABSTRACT

The authors are collaborating with a manufacturer of custom built steel frame modular units which are then transported for rapid erection onsite (volumetric building system). As part of its strategy to develop modular housing, Enemetric, is taking the opportunity to develop intelligent buildings, integrating a wide range of sensors and control systems for optimising energy efficiency and directly monitoring structural health. Enemetric have recently been embracing Building Information Modeling (BIM) to improve workflow, in particular cost estimation and to simplify computer aided manufacture (CAM). By leveraging the existing data generated during the design phases, and projecting it to all other aspects of construction management, less errors are made and productivity is significantly increased. Enemetric may work on several buildings at once, and scheduling and priorities become especially important for effective workflow, and implementing Enterprise Resource Planning (ERP). The parametric nature of BIM is also very useful for improving building management, whereby real-time data collection can be logically associated with individual components of the BIM stored in a local Building Management System performing structural health monitoring and environmental monitoring and control. BIM reuse can be further employed in building simulation tools, to apply simulation assisted control strategies, in order to reduce energy consumption, and increase occupant comfort.

Keywords: *Building Information Model, Enterprise Resource Planning, Modular Structure, Prefabrication, Volumetric Construction*

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1. INTRODUCTION

In an increasingly technology driven world where everything is beginning not only to be intelligent but also interconnected while also driven by green pressures (such as energy efficiency, life cycle performance and costs etc.), society is placing ever increasing demands on industry to improve their products by taking advantage of new technologies. At the same time, companies have to comply with increasingly stringent performance requirements imposed by the pressures of sustainability and climate change. As part of its strategy to develop modular housing, Enemetric (a small Scottish manufacturer of volumetric building systems) is taking the opportunity to develop intelligent buildings, integrating a wide range of sensors and control systems for optimising energy efficiency and monitoring structural health, while adopting a Building Information Modeling (BIM) approach throughout the design process and in the future, deploy BIM in construction and lifetime management. Furthermore, when combining BIM with real-time monitoring of energy consumption and structural health with simulation techniques (dynamic thermal simulation, on-line structural assessment) a robust and intelligent solution for managing modern buildings can be developed.

Modern information and communication technology enables unparalleled collaboration of systems and user groups, and a wide choice of sensor/actuator topologies in terms of wired/wireless layers. This is leading to a requirement to efficiently define methods of managing the explosion of data and more importantly, appropriately linking and making sense of the information logically.

Companies and practitioners currently promote BIM as a tool to share data between various user groups as a way of efficient dynamic work flow, and effective project planning, but the concept has tremendous weight as a technology for the building to manage itself by combining the static building data with the dynamic data generated from monitoring subsystems. In other words, BIM needs to be encapsulated in the Building Management System (BMS) layer, whereby the BMS has full knowledge of the BIM and is better equipped therefore to manage itself. The combination of the BIM data with building behaviour data collected by the BMS can help to predict scenarios (to optimise or mitigate) and with the provision of data on a community wide scale, techniques such as Demand Side Management make efficient shared resource allocation possible for renewable energy sources.

The structural robustness of the Enemetric modular systems under extreme loads such as earthquake and fire have been carried out using detailed finite element models. A BMS system with structural monitoring component has been installed in a sample house, with system identification being carried out through continuous real-time monitoring of ambient and forced vibrations, as well as energy and environmental monitoring with heating and lighting control. Full structural dynamic models and thermal models of the sample house have been constructed to help assist in developing integrated control and maintenance strategies. A BIM approach has been used, combining energy and structural monitoring, with optimising procedures, optionally assisted by simulation. These concepts shall be discussed.

2. TOWARDS A BIM MANAGEMENT SYSTEM

BIM evolved as a superset of the 3D CAD model of a building, containing parametric information supplemented with object relationships, which can support the simulation of a building virtually, permitting experimentation, by modification of design parameters. BIM is therefore, geared towards automating the creation of optimised buildings (in terms of energy use and structural design), and management of building data. However the current methodology does not include further methods of data collection and storage through online monitoring, and additional manipulation through data analysis in simulated models can help to improve performance or mitigate any problems during the building lifetime, when BIM is encapsulated in a Building Management System. This would also enable the automatic updating of building information models (Hwang & Liu, 2010) for continual self-diagnosis and reporting to aid 6D BIM, in terms of lifetime management. The main focus of BIM thus far has been interoperability between software and data re-use, particularly with design simulation tools, which up this point has been a successful reason for its recent widespread adoption in the AEC industry, especially in terms of collaboration.

Currently methods have been developed to automate the design process using BIM with an emphasis on energy efficiency and optimum structural design, and to further encapsulate BIM in the BMS layer to generate simulation assisted maintenance and control strategies. Furthermore, a BIM methodology proves to be useful for management of modular building structures and project planning.

2.1. Benefits of BIM for Volumetric Construction Workflow

Enemetric in collaboration with The University of Edinburgh, recently have developed ways of automating the design of modular structures using BIM, including new methods to automate the design of modular steel frames from existing architectural drawings. Previously this was achieved by hand, where a draftsman would meticulously work on several CAD drawings, creating the volumetric modular structure by dividing the building into variable sized rectangular cuboid modules, representing the steel frames. Once this stage is completed the drawings are passed to a structural engineer who would carry out the necessary structural calculations and design to conform to Eurocode regulations. Finally once the structure of the steel is determined, an estimation team will use the data to estimate the cost of the steel and materials, and pass on the details to the supplier to make any necessary orders.

This process, with data passing through several hands is time consuming, taking up to one working day. Now, using BIM methodology, only one 3D CAD drawing is required and the processes shown in Figure 1 are fully automated, using a single piece of software, with results produced in less than an hour. Techniques have been developed to mark out in the original CAD drawings, placement of individual modules, which when input into the software, full structural design is carried out using Finite Element Analysis, a detailed report is generated describing each module that makes the building, and a virtual mock-up is created in Sketchup, complete with internal framing and external finishing including windows and doors. Crucially, the software outputs the estimate for the steel, allowing for very rapid, accurate, quotations to be generated very quickly, reducing the time and cost of estimation prior to sales.

Further progress is being made to incorporate Computer Aided Manufacturing (CAM) used for the cutting of internal frame panels, eliminating a chain in the current workflow loop, blurring the differences between BIM, CAD AND CAM. As Enemetric are exploring ERP solutions, to improve business intelligence, interfaces are to be developed to the BIM software, to permit highly accurate estimation and planning with supplier databases and project management scheduling tools. (Figure 2)

Figure 1. Traditional enemetric workflow

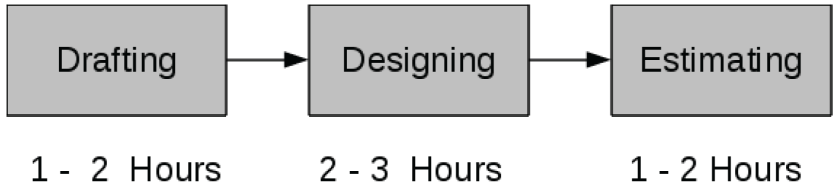
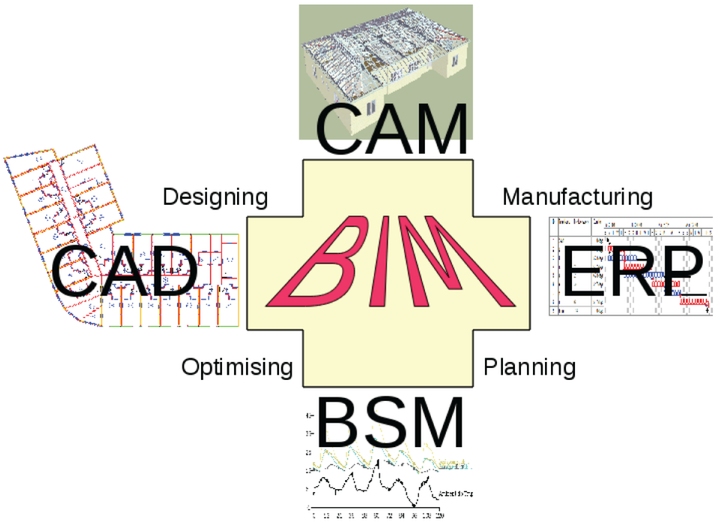


Figure 2. BIM can be used for designing, optimising, manufacturing and planning



BIM can also be used to generate Building Simulation Models (BSM) for energy and structural modeling to optimise the building during the design stages and can be used for Simulation Assisted Control, and further Structural Health Assessment in the Building Management System. Dynamic building simulation tools, such as ESP-r can be integrated into the BIM software, to introduce Energy Performance Ratings based on a intermediary meta-file file format method (Gauri et al., 2010), and can be further integrated into the Building Management System for lookahead simulation optimisation.

2.2. Enemetric ERP System

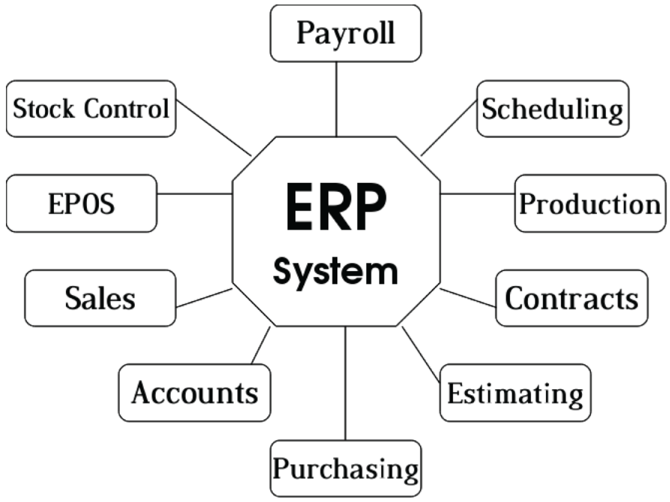
An ERP system controls and manages all the business operations. Linking BIM software to ERP has several beneficial impacts on the workflow, particularly for Estimating, Contracts, Scheduling and Production. Projects are directly based on individual BIMs, with each BIM having their own set of attributes, further decomposed into volumetric modules, each with their own timeline for production, requirements for resource and relevant budgets. (Figure 3)

In terms of Estimating, the BIM software will communicate directly with the ERP Stock Control database, to retrieve accurate pricing for building components such as windows, doors, steel and HVAC systems of items either in stock or to be placed on order from other suppliers. This can yield a highly accurate up-to-date estimate (5D BIM). The estimate can then be used to provide a complete budget, including sub-contract work, which can then be used to develop quotes to tender bids for the Contracts database of the ERP system. Resource requirements are planned using the Scheduling component of the ERP system, whereby detailed schedules and project plans can be produced (4D BIM).

2.3. Object-Oriented BIM and Data Structures for Modular Buildings

The management and manipulation of BIM data is possible with object oriented data modeling, whereby the building can be composed of many elements (objects) which have various relationships. Enemetric adopt a modular method of construction, making logical associations important on a number of levels, not only structurally, but also in terms of energy and construction; a whole building object is composed of many module objects and each module has a structural relationship with adjacent modules. Each module is made up of beam objects, with internal steel framing objects, with load requirements. Rooms can be considered objects, as are windows doors, floors etc. In terms of energy balances, rooms will have relationships with

Figure 3. Elements of an enterprise resource planning system



other rooms, with respect to heat transfer. Each room itself will contain objects for lighting, heating, etc. There will be sensor and actuator objects and relationships. One sensor object may be related to several actuators (Motion sensor for light control, or intruder alarm). Room objects may belong to several module objects, and so forth. Each module will have various priorities for fitting of services or furnishings. Building data like this and object relationships can be modelled in data structures such as IFC (Industry Foundation Classes) or markup language XML (Green Building gbXML). The collection of data objects and their relationships is the central feature of the Building Information Model. Both standards offer benefits for modular BIM data structures, with IFC enabling tightly coupled relational data, and gbXML offering a readable XML based format which can be extended (Dong, Lam, Huang and Dobbs, 2007). The readability of XML has pushed the industry towards creating further schemas, such as ifcXML and agcXML. A modular BIM XML schema would prove to be beneficial as a readable data source for building projects at Enemetric, providing interoperability between CAD (gbXML to test design ideas in various drawing tools), CAM (XML for CNC cutting), BSM (gbXML intermediary format for dynamic thermal simulation, whole building simulation, or structural finite element analysis) and ERP (XML Project Management -PMXML.)

3. BIM, MONITORING AND MODELLING

3.1. Structural Design Modelling and Estimation

The Enemetric BIM software contains conventional structural design procedures. First, the software will perform Finite Element Analysis on the geometric model supplemented with external loading input. Using the Finite Element Analysis results, the software designs cross-sections and structural members according to Eurocode ultimate and serviceability limit states, and lowest potential cost, taking into account smaller cross-sections are more desirable. The stress and deformation of all structural components undergo a resistance check, and finally the weight and cost of the complete structure is output.

The Finite Element Analysis component of the Enemetric BIM software differs from commercial structural design packages, which can be complex to use, requiring several layers of detail. Using conventional packages would require detailed construction of the structure's individual elements, specifying locations and materials of each member, and most importantly, an accurate representation of the interconnections between modules. Doing so by hand is time-costly, error-prone and tedious.

Enemetric's BIM software however only requires a modified DXF format plane drawing, where modules are simply represented as crossed lines. The software can then directly construct a Finite Element model, including preliminary design cross-sections, additional middle beams and columns, according to previous design experience. External walls are automatically designed by the package, while internal walls, windows and doors can be input in the same DXF file; therefore the file contains both architectural and structural cues in terms of building information. Figure 4 shows a sample input drawing of the BIM system. Beyond an accurate cost estimation produced by the software, further outputs include a structural design report and the foundation action report. The reports provide detailed calculation procedures for permanent action, wind loading, bending resistance and deflection checks for columns and beams, while calculating foundation reactions due to various loading combinations. The reports are based on a variation of Enemetric's own conventional client report. Included in the reports, are conventional order files suitable for the material supplier. Refined structural and architectural plane drawings are also output in an AutoCAD format, as shown in Figure 5 and Figure 6; precise and detailed 3D model are also constructed automatically in Sketchup, shown in Figure 7, Figure 8 and Figure 9.

More than twenty practical modular buildings have been designed and estimated by the BIM software, and demonstrates a high accuracy (98%) of cost estimation when compared to conventional hand derived design procedures. The construction cost estimation of the complete modular building includes the costs of the structural and surface components, isolation materials, windows and doors, giving the designer a clear idea of the total cost and investment margin of the building very early in the design stage.

The lightweight steel structure is composed of a number of substructures in the modular building, including the floor, roof, external and interior walls, which are required to be

Figure 4. DXF format plane drawing input to the BIM

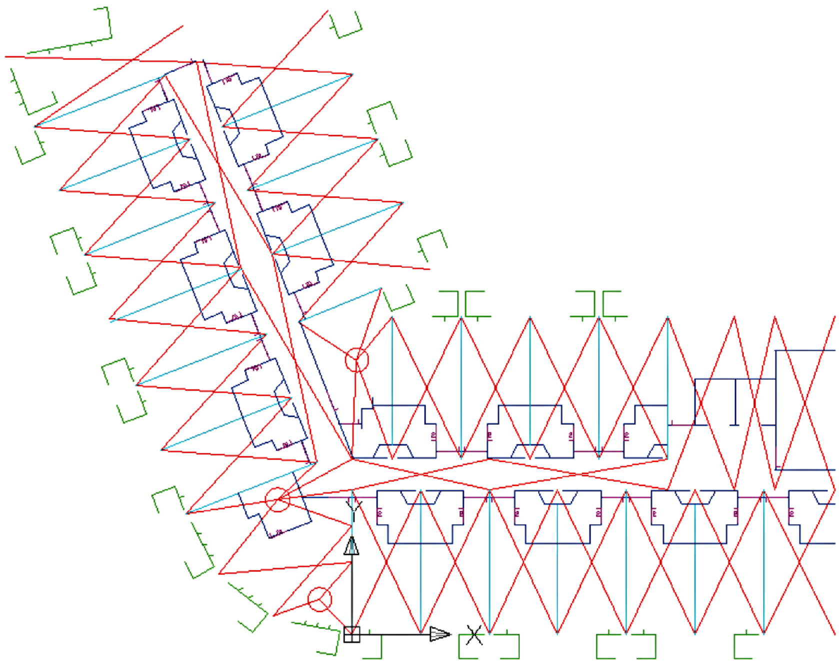


Figure 5. Building plan and 3D model generated by the BIM: Building plan

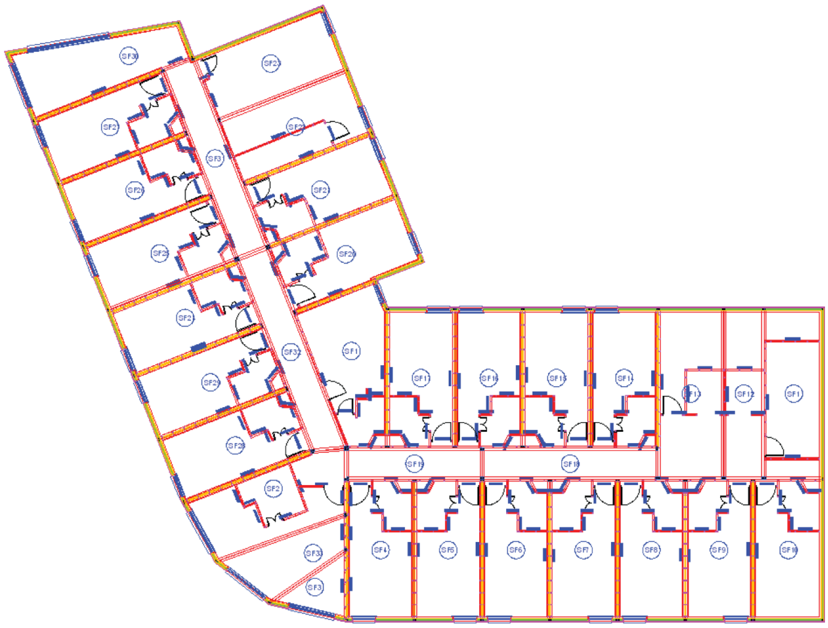
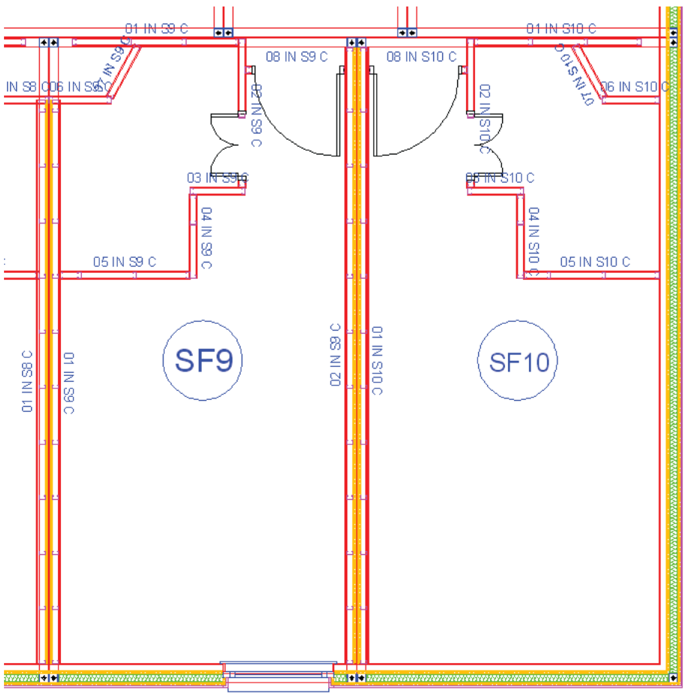


Figure 6. Building plan and 3D model generated by the BIM: Details in building plan



prefabricated by CAM machine tools. One of the recently developed BIM functions allows automatic generation of the controlling file for the CAM system, which can achieve a high level of factory automation. (Figure 10)

3.2. Building Simulation Modelling

Traditional building energy modelling software such as IES and ESP-r, have complex methods of creating buildings to be simulated for energy

Figure 7. Building plan and 3D model generated by the BIM: 3D model

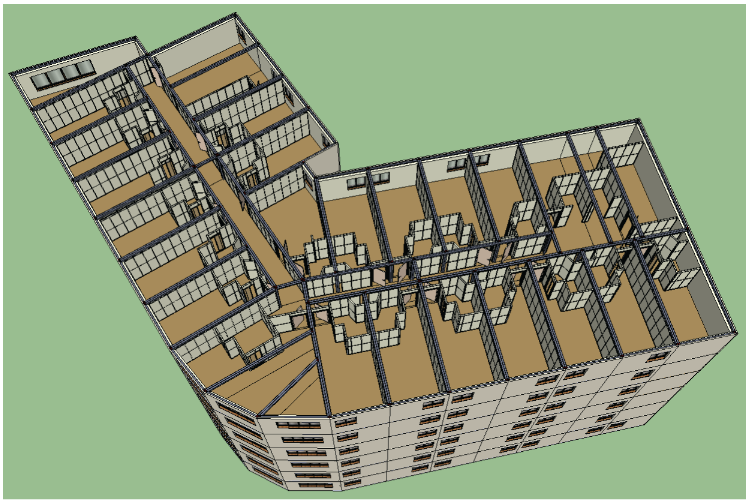


Figure 8. Building plan and 3D model generated by the BIM: Perspective view

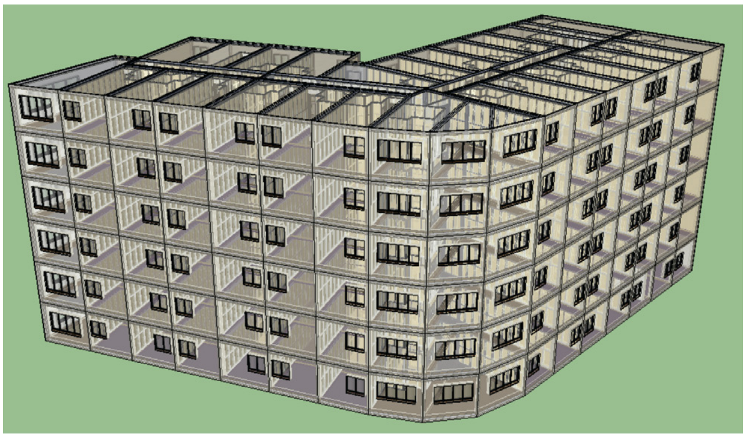
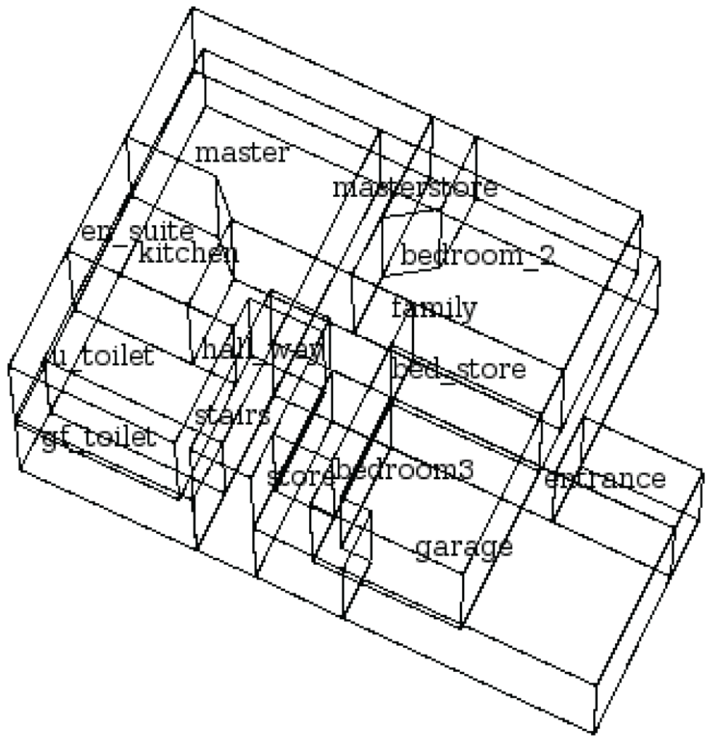


Figure 9. Building plan and 3D model generated by the BIM: Building on the exact location in Google maps

Figure 10. This ESP-r model of the sample house was created by hand-drawing on 2D floor plans



balances, and heating loads. Particularly with ESP-r there is no 3D drawing tool, as with modern CAD systems, but only textual input of coordinates, or drawing on 2D floor plans, where mistakes can easily be made. By leveraging the existing BIM data into a simulation tool directly, where relationships already exist between various room objects, including detailed information down to the construction materials used for various wall layers (insulation, etc.), highly accurate results can be obtained. Intermediary data structures such gbXML are used to achieve this, but it would be useful to have these functions integrated in a complete integrated BIM package for modular buildings using the meta-file format discussed previously. In this way, Energy reports can be created as the building is being designed instantly during design phases.

3.3. Building BIM Monitoring

Alahmad et al. (2010) have discussed integration of BIM with real-time power monitoring. They had found that BIM in its current state cannot provide 'online information detailing' and proposed a Real Time Power Monitoring System as a solution. The benefits of such a system include creation of detailed energy-consumption databases and load profiles, suitable for effective Demand Side Management (DSM). Therefore not only are these monitoring benefits suitable for the user, who can access online feedback of consumption of individual devices and control their own behaviour, but also for intelligent systems that can optimise the energy management through smart grid networks. Such a system goes beyond passive smart metering by implementing active energy management. The system could monitor large energy consumers in the building and use weather prediction and dynamic building simulation to anticipate occupant's needs and apply optimal control strategies for energy efficient heating, lighting and other building loads. Smart Meters alone cannot actively manage energy, requiring an energy management system component to take advantage of the two-way communication to reduce power consumption of devices. Self-reporting is also important for energy analysis to verify energy performance in different phases of the building, permitting continuous verification of the whole building life cycle (Laine, Hanninen, & Karola, 2007). The monitoring BIM contains detailed information regarding sensor and actuator relationships, current values in terms of structural health, environment, such as temperature and humidity, load characteristics of HVAC systems and efficiencies relating to energy losses particularly with rooms with no occupancy. The building should not be delivering energy to persistently unoccupied areas, and using occupancy data from PIR sensors, the self-reporting element of the BIM can monitor lighting and heating loads in those areas. Examples of real-time monitoring systems developed in the sample house BMS are shown in Figure 11) relating to vibration characteristics, in terms of measured accelerations (structural health) and Figure 12) showing real – time breakdown of energy consumption (power monitoring). The sample house BMS performs structural health assessment by measuring accelerations from Arduino based sensors attached to floor beams, and a database keeps a recorded state of the overall health of the BIM structural model. The real-time breakdown of energy is updated every 6 seconds from Current Cost energy monitors, giving a quick overview where energy is being most consumed, allowing reduction strategies to be developed.

3.4. BIM in the Building Management System Layer

Use of BIM does not need to end at the initial design or construction stages but needs to continue throughout the lifecycle of the building and find a place within the Building Management System (BMS). Incorporating the BIM into the BMS can help design the management system in terms of sensor/actuator relationships and by further combining the relationship with actual monitored data, intelligence can be created with on-line simulation control strategies and provide fault detection and diagnostics (Provan et al., 2009). Importantly, for structural analysis and fault detection, a structural health monitoring system can update a structural BIM model, to determine overall building structural health, particularly for earthquake regions, or overloads in large crowd loading scenarios. Furthermore,

Figure 11. Online monitoring shown in webpage. Real time accelerations.

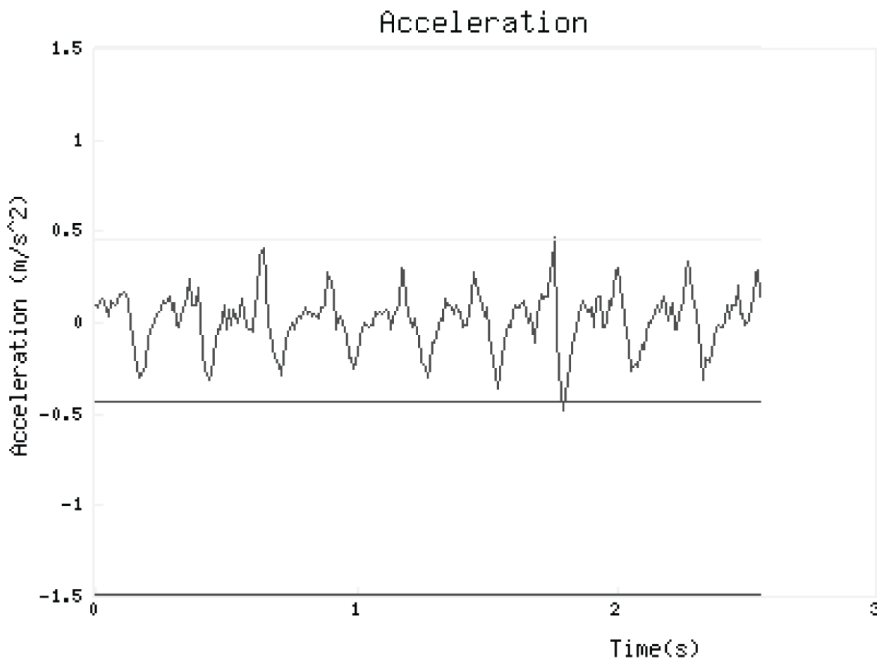
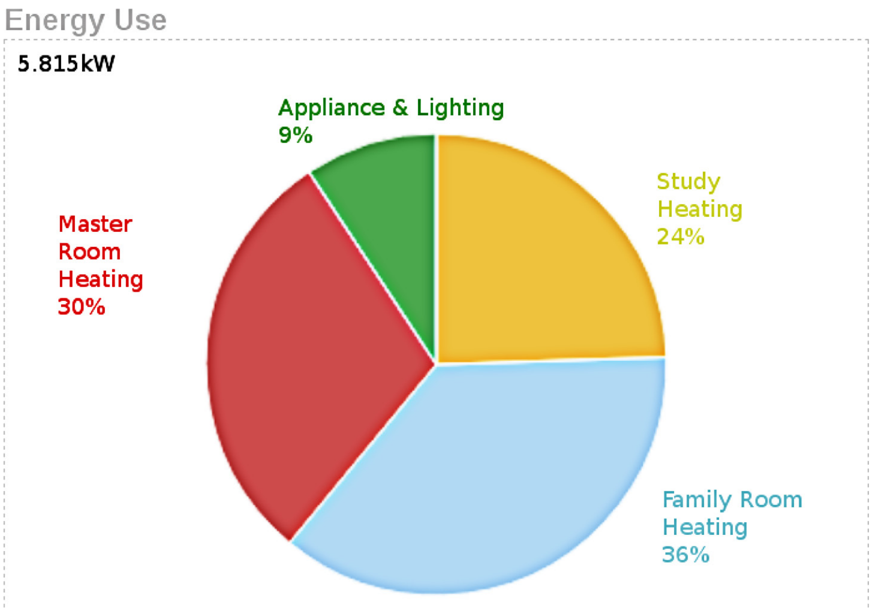


Figure 12. Online monitoring shown in webpage. Real-time energy-consumption.

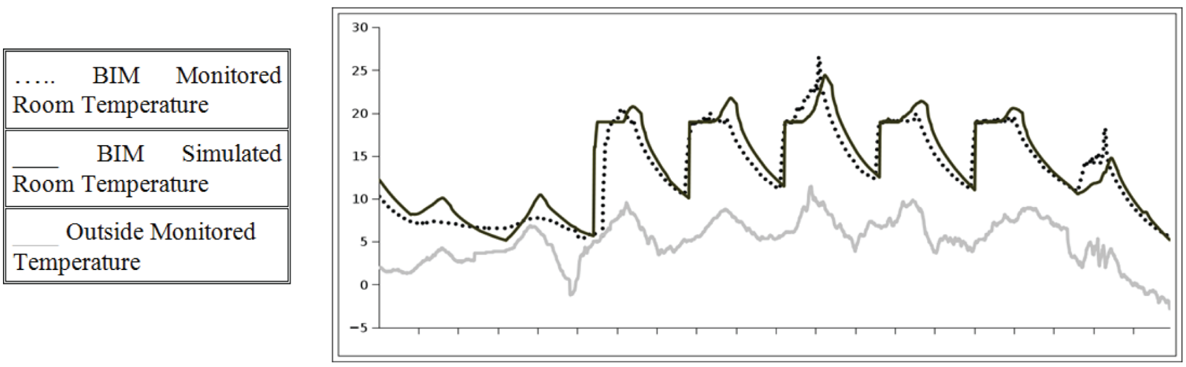


in terms of a Building Simulation data model, monitored data can be fed into a simulation tool to predict various outcomes of different scenarios to optimise energy use. This is particularly useful for energy consumptive services such as HVAC, where simulations can be run to ascertain optimum start-up times for the heating system. This intelligence, gives the ability to make the best decisions, based on monitored and predicted data on full scale models, leading to better control and maintenance outcomes

Current methods of intelligent learning in buildings, such as Neural Networks require significant amounts of training and are not useful beyond their range of experience. Building simulation though, is essentially a virtual representation, permitting a more accurate set of prediction outcomes and thus more energy efficient control strategies. Coupled with smart grid technologies, such a system would also be able to perform automated demand response for energy reduction and management. With the BIM encapsulated in the BMS, the system would require prediction data, such as Weather Forecast Models, obtained from internet feeds.

Figure 13 demonstrates successful integration of the BIM simulation model in the BMS, by supplying monitored data (outside temperature, direct solar radiation, humidity) directly into the ESP-r simulator. Good agreement has been

Figure 13. Daily temperature response simulated and monitored



achieved between the simulated and monitored results, verifying the use of the simulator for prediction. Having an accurate BIM simulation model is important for anticipating demands and future load requirements for the BMS, particularly under extremities and to perform simulation assisted control strategies or global structural health assessments.

4. FURTHER WORK

Further work to be carried out in the future to enhance the system include concepts such as on-site erection management for the logistics and transportation of modules, installation equipment and labour; Material ordering based on prediction, particularly for steel; Design of pipeline systems for electrical, network and plumbing systems, which require special considerations due to the modular design; And lastly modelling from conceptual design, using an expert system to support the design, while minimising user input. To support the above it is hoped a Modular Monitoring BIM XML data structure will be developed internally to support Enemetric's workflow and development of integrated intelligent building management systems in future construction projects.

5. CONCLUSION

We have discussed the application of BIM in volumetric construction for modular buildings, and the relationships with resource planning, optimal design, computer aided manufacture and simulation assisted control with BIM encapsulation in Building Management Systems. The BIM software that has been developed is constantly undergoing revisions to incorporate further functionality and has been a successful demonstration of knowledge transfer between The University of Edinburgh and Enemetric. The estimation tools in particular have had a significant impact in improving the work flow, from design to manufacture.

It is hoped that in the future, higher degrees of automation will be achieved, with the potential for robotic manufacture, and that the software may evolve into a house or building configuration tool, and incorporate elements of customisable homes, which would complement the modular method.

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AN INTEGRATED MONITORING SYSTEM FOR MODULAR BUILDINGS

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The authors are collaborating with a manufacturer of custom built steel frame modular units which are then transported for rapid erection onsite (volumetric building system). A bespoke integrated monitoring system is under development for control of all systems in the building (such as efficient energy usage, lighting, security and comfort) as well as the monitoring of structure. The former could be achieved by buying in existing technology, however these tend to be costly, single supplier, closed systems that have limited interoperability. Furthermore, there are no systems available that will easily integrate structural health monitoring with monitoring for controlling building systems. As the structural system is relatively lightweight, the vibration characteristics are of interest from a noise insulation point of view. The paper describes all aspects of the integrated system and presents a selection of results from early tests carried out to assess the integrated system.

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AN INTEGRATED MONITORING SYSTEM FOR MODULAR BUILDINGS

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ABSTRACT: The authors are collaborating with a manufacturer of custom built steel frame modular units which are then transported for rapid erection onsite (volumetric building system). A bespoke integrated monitoring system is under development for control of all systems in the building (such as efficient energy usage, lighting, security and comfort) as well as the monitoring of structure. The former could be achieved by buying in existing technology, however these tend to be costly, single supplier, closed systems that have limited interoperability. Furthermore, there are no systems available that will easily integrate structural health monitoring with monitoring for controlling building systems. As the structural system is relatively lightweight, the vibration characteristics are of interest from a noise insulation point of view. The paper describes all aspects of the integrated system and presents a selection of results from the early tests carried out to assess the integrated system.

1 INTRODUCTION

In an increasingly technology driven world where everything is beginning not only to be “intelligent” but also “interconnected”, while also constrained by “green” pressures (such as energy efficiency, life cycle performance and costs etc.), society is placing ever increasing demands on industry to improve their products by taking advantage of new technologies. At the same time, companies have to comply with increasingly stringent performance requirements imposed by the pressures of sustainability and climate change. As part of its strategy to develop modular housing, Powerwall (a small Scottish manufacturer of “volumetric building systems”) is also taking the opportunity to develop “intelligent buildings” by integrating the control of all systems in the building (HVAC, lighting, telecoms, security etc.) with structural monitoring. The monitoring of the building’s internal and external environment by the building intelligence would enable optimisation of occupant comfort in an energy efficient manner as well as ensuring their safety and security. There is also the opportunity to provide continued service, repair and maintenance through remote monitoring of the building through a service hub. In addition the company aims to provide this value in a sustainable manner at life cycle costs much lower than conventional building systems. While these technologies already exist for high value buildings, very few companies have investigated such systems for incorporating into ordinary domestic dwellings in a cost effective manner.

The pace of development of building intelligence has stepped up considerably over the last decade with open communication standards such as BACnet and LonWorks maturing, Snoonian (2003). However, such systems remain too expensive for mass installation in budget housing, thus an in-house system has been designed specifically for Powerwall modular buildings. A development system has been installed in a test house that the company has constructed using its volumetric system. The monitoring system is constructed using a combination of a wired network (1-wire) and a wireless system (Z-wave), which has enabled robust measurement of many environmental variables such as power use, external & internal humidity, external solar radiation (luminance), indoor CO_2 as well as interior and exterior temperatures of the sample house. A weather station houses and protects the sensing equipment for humidity and luminance measurement. Work has also progressed towards development of user-friendly human-computer interfaces that work on a web browser from laptops or handheld smart devices.

The structural robustness of the modular systems under extreme loads such as earthquake and fire have been carried out using detailed finite element models and design modifications are being developed and implemented. The structural monitoring system is currently under discussion and will include monitoring for structural robustness and for long term maintenance. Once structural monitoring is installed in the sample house, system identification will be carried out through monitoring ambient and forced vibrations. Full structural dynamic models of the sample house will be constructed and updated to assist in developing integrated control and maintenance strategies.

2 THE BUILDING SYSTEM AND STRUCTURAL ANALYSIS

Lightweight steel is increasingly used in modern building construction. Apart from pre-fabricated structural components such as curtain walls, ceilings and floors, self-contained modular units are also being developed. Building systems constructed by assembling modular units are sometimes called open house system, Veljkovic and Joahansson (2006), volumetric structure, Powerwall (2008), or modular steel building, Annan *et. al.* (2009). The advantages of module systems include higher accuracy and efficiency of production, shorter construction period, reduced use of skilled labour for on-site work, lower life-cycle cost, reduced construction waste, and thus generally improved sustainability.

In this study, a novel modular system, referred to herein as post-tensioned modular system (PTMS), is considered, Powerwall (2008). The system is constructed by assembling modular frame units through special diecast connectors at the floor levels and using tie rods vertically. The post-tensioned tie rods tightly connect the modules and also provide a mechanism for lateral load resistance in conjunction with the connectors. Because of unique structural features due to the pre-stressing system, the structural system requires special modelling considerations.

Figure 1. Building structure made from modular units and tie rods (courtesy Powerwall 2008)

Zheng *et. al.* (2011) carried out a detailed local and global analyses of the structural system subjected to lateral (wind or seismic) loads and suggested design modifications. The complexity of the contact behaviour between individual modular frame units and the connecting tensioning rods was modelled using a number simplifying idealisations which conserved the essential features of behaviour. The tie (post-tensioned) rods were modelled using tension only bar elements. The post-tensioning force was introduced by setting an initial tensile strain in the bar elements. The contact between the modular frame units in the vertical direction was modelled using mass-less, rigid and compression only bar elements. The connection between the tie rods and connectors was also modelled using compression only bar elements. The analyses identified three main failure modes for the system: failure of tubular components in the frame, with buckling of a tubular column or bending failure in columns/beams; rupture of tension rods; and, connection failure at the joints caused by local failure in the tubular columns around the connectors.

3 INTELLIGENT BUILDING MANAGEMENT SYSTEMS

3.1 Current State of the Art

Building Management System (BMS) Solutions are almost exclusively targeted towards larger buildings, with few solutions for smaller residential homes (Smart Home Solutions), which tend to be aimed towards luxury installations. They are used to monitor, control and manage systems and facilities for HVAC, Lighting and Security. Early incarnations used proprietary protocols for communication between sensors and actuators; nowadays manufacturers give options for protocols such as BACnet and LonWorks allowing a degree of integration between systems. It is this integration that enables intelligence within buildings, so that data can be shared between different systems. Advanced monitoring is now possible with the proliferation of web access and mobile devices. It is said that more intelligent control of buildings and systems may yield savings of 20% in energy consumption, Murakami *et. al.* (2007). In order to maintain a BMS in an optimal state, expert knowledge is required to interpret monitored data and identify how to save energy, minimise costs and provide the best comfort to occupants. A building can be considered a living entity, a form of intelligence that seeks to improve itself to perform efficiently and provide the best level of comfort for its occupants. Though there are several technologies that support building intelligence, there is still a lack of 'self-awareness', whereby the building adapts to its use and the environment producing an optimum level of performance in terms of functionality and efficiency.

As the field of structural health monitoring matures, it would make sense to integrate SHM and BMS, particularly so for smaller buildings. The authors are unaware of any such integration in the context of buildings however such systems do exist for aircraft, Gorinevsky *et. al.* (2005). If a building could store information about itself, in the form of a model and how it interacts with internal and external conditions, the BMS would be able to make decisions about how to deal with day to day operations, without human intervention. Humans should only need to be alerted of potential problems and faults or events detected by the BMS (such as seismic excitation), and not have to concern themselves with daily operation and optimisation. Other advances in Building Modeling and Simulation have yet to cross over to Building Management Systems and create a true Intelligent Building. Though there are solutions that have integrated Building Information Modeling (BIM) with BMS in terms of 3D visualisation, floor planning and design of plant (the BIM concept has roots in 3D CAD), simulation has yet to have an impact beyond design stages, even though the same BIM data can be used throughout the building lifecycle, from initial conception during design to maintenance strategies for repairs or refurbishment. The benefits brought forward by dynamic simulation integrated into the BMS has been a relatively small research area, potentially offering massive benefits. These will be highlighted in following sections.

3.2 Simulation & Simulated Assisted Control Strategies for Building Management Systems

Building simulation software is increasingly being employed by architects and facilities managers to model performance of a building and its energy use. Recent developments in BIM look to integrate CAD software with energy performance tools to aid design of energy efficient buildings. Simulation allows a range of building physics problems to be applied to a building model and analysed, particularly thermal loads (e.g. ESP-r), lighting luminance (e.g. RADIANCE) and structural deformations (ANSYS, ABAQUS). The building can essentially be prototyped virtually, and various profiles of use can be applied, in order to make control and design decisions. It is said that decisions made early in the building design process, based on simulation results, can have a substantial impact on the building performance[7]. Of particular importance are, heating and cooling strategies, which dominate the decision process for energy performance, as they form the majority of energy demand in a building. Example strategies include Optimised Start/Stop for heating systems and Optimum Night Set Back Temperature. Such strategies require to be implemented in the BMS. However, even a well implemented BMS is still developed from design parameters, and over time these initial parameters will no longer hold true, as the building use changes. These changes can be seasonal, in which case the BMS needs to be reprogrammed to a winter or summer operating mode. Furthermore with climate change shifting seasons it becomes more difficult to predict extreme weather conditions such as a harsh winter. Even though a BMS may be pre-programmed to anticipate seasonal changes, occupant usage changes, equipment use and knowledge of internal furnishings is impossible to determine. BMS can have complex monitoring abilities, and skilled operators will be needed to assimilate the data and make adjustments. For very large buildings, this may require dedicated staff, but in a residential setting, this simply is not possible. The ability to adapt, by applying intelligence to the BMS will enable automatic configuration without an operator, a feature that could be a form of self-learning. Previously much research in this area (model predictive control), has focused on neural networks and other prediction techniques. These techniques have been found implemented in commercial systems (Yoga Intelligent Buildings applying neural network theory), however, lack of initial knowledge, and the time to acquire it can affect the efficiency. This can be achieved with simulation. Simulation permits larger data sets to be used and real-time computation to aid control.

3.3 Building Information Model (BIM)

BIM is a relatively new and exciting paradigm in the construction industry, and is a method of generating and managing building data using software. Information about a building is held in a central repository. Various models can be derived, such as a cost estimate model, 2D/3D CAD drawings, energy and seismic analysis, etc.

A BIM is a superset of the 3D CAD model of a building, containing parametric information supplemented with object relationships, allowing comparisons and analysis to be made. The additional data contained within the BIM can be used to create further models and useful information. 4D Models contain time information such as project scheduling. 5D Models add a further cost dimension, including labour and construction costs, with respect to the 4D plan. 6D Models add MEP (Mechanical, Electrical & Plumbing), and may also include equipment details, such as maintenance scheduling. This is otherwise known as Lifecycle Management.

4 PROPOSED SYSTEM ARCHITECTURE

4.1 Base system for building intelligence

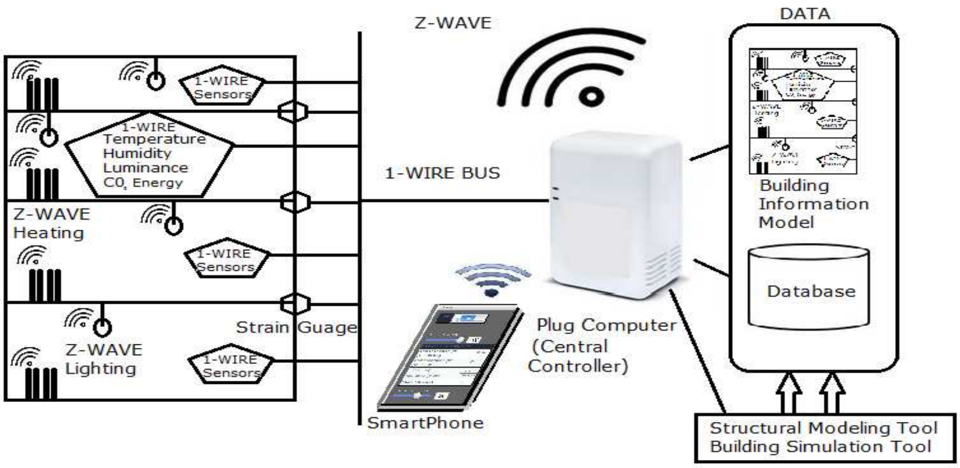


Figure 2. Building Intelligence Architecture

Figure 2 shows the proposed system architecture. The building intelligence platform itself has been designed to be considerably more energy efficient in comparison to commercial BMS systems, which can themselves consume a lot of energy while trying to save it. An embedded 'Plug Computer' has been chosen as the central controller hardware; essentially an extremely small form factor Linux (Debian), computer packaged into the size of a small AC adaptor. Consuming less than 5W, and with a hardware specification including a 1.2Ghz processor and no moving parts, makes it a robust processing unit that requires to run continuously and provide all the monitoring and control duties that is required from a BMS. The Plug Computer interfaces to both wired and wireless sensor networks. 1-Wire permits a diverse networking bus structure, whereby a single cable can be used to both transmit power and data, making it an energy efficient wired solution, particularly for continuous sensing. Z-Wave was chosen as the wireless protocol for control of lights and heating thermostats, as it operated in a different frequency band to commonly installed WiFi systems (IEEE 802.11) and also to Zigbee (IEEE 802.15.4), and offered a wide range of equipment options for the chosen services. Measurements are taken every minute and stored in a database (RRDTool), which also provides comprehensive graphing functions. A Building Information Model (BIM) is stored in a separate database, containing the building's geometric, structural and thermal properties, which can be used to perform on-line simulation via a building simulation tool (ESP-r) to generate energy efficient control strategies, and a structural modeling tool developed at Powerwall to continually assess the building's structural health. The BIM is continually updated and calibrated to reflect the building's properties virtually, which can also be downloaded remotely, so that further analysis may be performed, including more computationally intensive simulations (e.g. earthquake simulation) on more powerful hardware.

4.2 Structural monitoring components

The monitoring system is intended to provide a real time structural safety and serviceability assessment of the modular structure, particularly when it is subjected to extreme loading scenarios, such as an earthquake or high wind. Two levels of structural monitoring are being considered.

The base level will involve the monitoring of the conditions related to the critical modes of failures identified by the structural analyses. This will include strain in the tension rods, primary floor beams and columns for the structural safety monitoring. The current building intelligence platform does not have the capacity to monitor structural vibrations. A stand alone vibration monitoring system is being considered to collect and locally store high frequency time series data and communicate appropriately filtered data to the BIM system.

The higher level will include an expert system to process the structural monitoring data acquired from the sensors and carry out safety and serviceability assessment. This will provide structural maintenance and repair recommendations for each building due to aging or extreme loading history. All structural monitoring and processing information will be provided to users and service engineers through an appropriate interface on the BIM system.

5 PROGRESS SO FAR AND REMAINING WORK

The current monitoring system has been successful in data acquisition, storage and

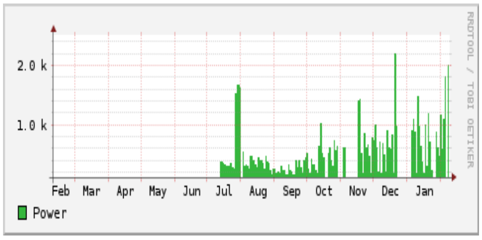
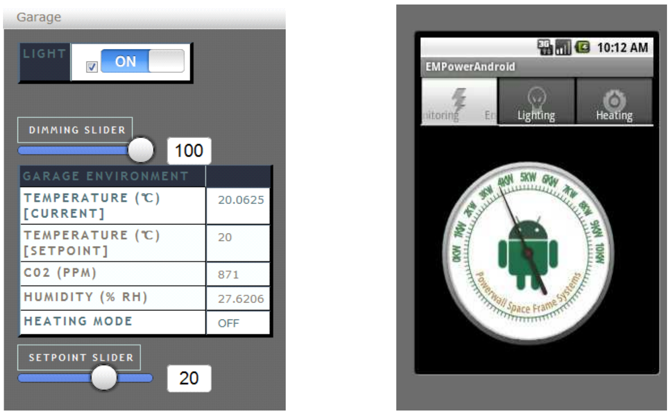


Figure 3. Energy Monitoring

representation, allowing the occupants to monitor their behaviour, particularly energy use. Figure 3 shows the increases in energy during the winter months due to additional heating requirements last year. The energy consumed during this period is hoped to be significantly reduced, by employing simulation assisted control to generate optimum heating strategies. By integrating the building simulation tool, ESP-r, to dynamically compute thermal loads based on real-time measurements, significant energy improvements can be gained by supplying heating only as required.



(a) (b)

Figure 4. (a) iPhone interface showing room monitoring and controls and (b) Android phone interface showing real time energy monitoring.

Other monitoring capabilities include external & internal luminance measurements allowing calculation of the daylight factor, to adapt lighting conditions dynamically depending on the amount of daylight in a room. An iPhone interface can be used to monitor and adjust lighting and temperature in each room (Figure 4a). Similarly an alternative Android interface has been developed (Figure 4b). These devices can also act as useful mobile alerting systems.

Presence detection is determined using PIR (Passive Infra-Red) movement sensors, and is used to control courtesy lighting. However to ascertain persistent occupancy, CO_2 monitoring (usually used to assess air-quality) will be evaluated in combination with PIR, to determine when to turn off lighting and heating when rooms are unoccupied (currently scheduled). Also under evaluation, is the use of adaptive comfort temperatures which aim to set them lower during winter months, based on the principle that occupants will adapt their clothing based on external temperatures.

A large amount of work has been carried out in automatic creation of optimised volumetric structures visualised in the 3D CAD tool, Google Sketchup. The software developed automatically designs and draws volumetric modules, with further options for walls, floors and roof design, with 4D and 5D BIM capabilities, proving useful in project management. This dramatically saves time, and the same data generated is used for initial creation of the BIM to help create the Building Simulation Model for ESP-r. This is of particular importance for a self-configuring BMS, which is already knowledgeable for its structure from initial installation.

Upon completion of the structural monitoring system, plug-ins will be created in Google Sketchup to visualise the results of the expert system in 3D, highlighting any structural components that may require maintenance. Later a bespoke 3D visual system will be integrated as part of the BMS, to be visualised on mobiles and tablets (possibly with augmented reality components) completing the integration task, and offering a complete intelligent and future proof system.

6 CONCLUSIONS

The paper presented the mid-stage progress of a project to develop an affordable building intelligence system which will integrate structural monitoring. The progress so far has been promising as a low-cost architecture has been developed and partially tested. Considerable work remains, particularly for the structural monitoring part of the system and the comprehensive testing of the integrated system on the sample house constructed to demonstrate the prototype system.

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